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Modeling Adoption of Solar Photovoltaics and Analysis of Net Metering in the City of Austin

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Modeling Adoption of Solar Photovoltaics and Analysis of Net Metering in the City of Austin

by

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Thesis

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Dedication

Dedicated to my family.

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I would not be the person I am now without the love and support from my family, I am grateful to them for all the encouragement. My peers and friends in Austin, grad school would not have been as much fun without you.

August 2011

Abstract

Modeling Adoption of Solar Photovoltaics and Analysis of Net Metering in the City of Austin

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The University of Texas at Austin, 2011

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Solar photovoltaics have received government support in the form of rebates, tax credits and net metering tariff mechanisms. The intended goal of these incentives is to encourage innovation in the manufacturing and installation of these systems, which is expected to eventually help overcome the high cost barrier for the adoption of the technology. These systems have the advantages of abundant availability of the solar resource, low environmental footprint, and the possibility of onsite installation, reducing the need for additional generation and transmission capacity. Since millions of dollars have been invested in these incentive programs, there is an interest in tracking the progress in the cost and capacity installed.

In the first part of this thesis, I analyzed the trends in costs and adoption of solar PV by residential and commercial customers in the city of Austin. This is accomplished

by tabular and graphical analysis of data on PV installations from 2004, when Austin Energy's rebate program started, to early 2010.

In the second part of the thesis, I used technology diffusion models to analyze and forecast the diffusion of residential PV systems in Austin. Three types of models were used to model the adoption trends: Logistic growth model, Bass model without price effects and Bass model including price effects.

In the final part of the thesis, I analyzed the net metering tariff mechanism in Austin and studied the difference between the current and an alternative tariff. The alternative tariff uses actual 'grid usage' to calculate the energy charge (cost of providing distribution service) instead of the 'net energy consumed' that is currently in use. Using simulated PV generation data and ERCOT load profile data, I calculated the difference in revenue for Austin Energy with the alternative tariff. The results indicate that the alternative tariff adds little revenue to Austin Energy's energy charge revenues at the current level of penetration of solar PV. However, at a higher penetration level of PV, the alternative tariffs might result in significant additional revenue for the utility. The thesis concludes with a discussion on the possible rationale for the alternative tariff and directions for future research.

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Chapter 1: Introduction

1.1 Background

In the strategic plan for Austin Energy in 2003, as part of the Energy Resource strategy, the city council committed to seek to meet new demand in the city through renewable energy and energy conservation solutions before resorting to fossil fuel based energy sources. The city council approved a 20% target for renewable energy and 15% target for demand side management (DSM) by 2020.

Specifically within renewable sources, the council proposed a strong commitment to solar energy by administering a solar PV rebate program starting in 2004, which at that time provided the highest rebate level in the United States. Some other initiatives to encourage development of solar energy are: a commitment to continue the rebate program for at least ten years; public awareness and education programs; and setting up of solar goals[1].

Year	Solar Goal (Cumulative MW)
2007	15
2010	30
2014	50
2020	100[2]

Table 1.1: Solar goals in Austin Energy's Strategic plan, 2003

Table 1.1 shows the initial solar goals set up in the strategic plan in 2003. These figures have been revised over time, and in 2011, the city revised the 2020 target to 200

[1] Austin Energy's Strategic Plan, December 4, 2003.

[2] As of March 2011, the capacity target for 2020 has moved up to 200 MW.

MW of installed capacity. In February 2011, the city council approved the Resource, generation and climate protection plan that set a target of 35% of annual energy supply from renewable sources and 800 MW of energy efficiency measures by 2020.[3]

Austin Energy's service area extends beyond the city limits to areas in the Travis and Williamson counties in Texas. Illustration 1.1 shows a map of the service territory along with the city limits of Austin.

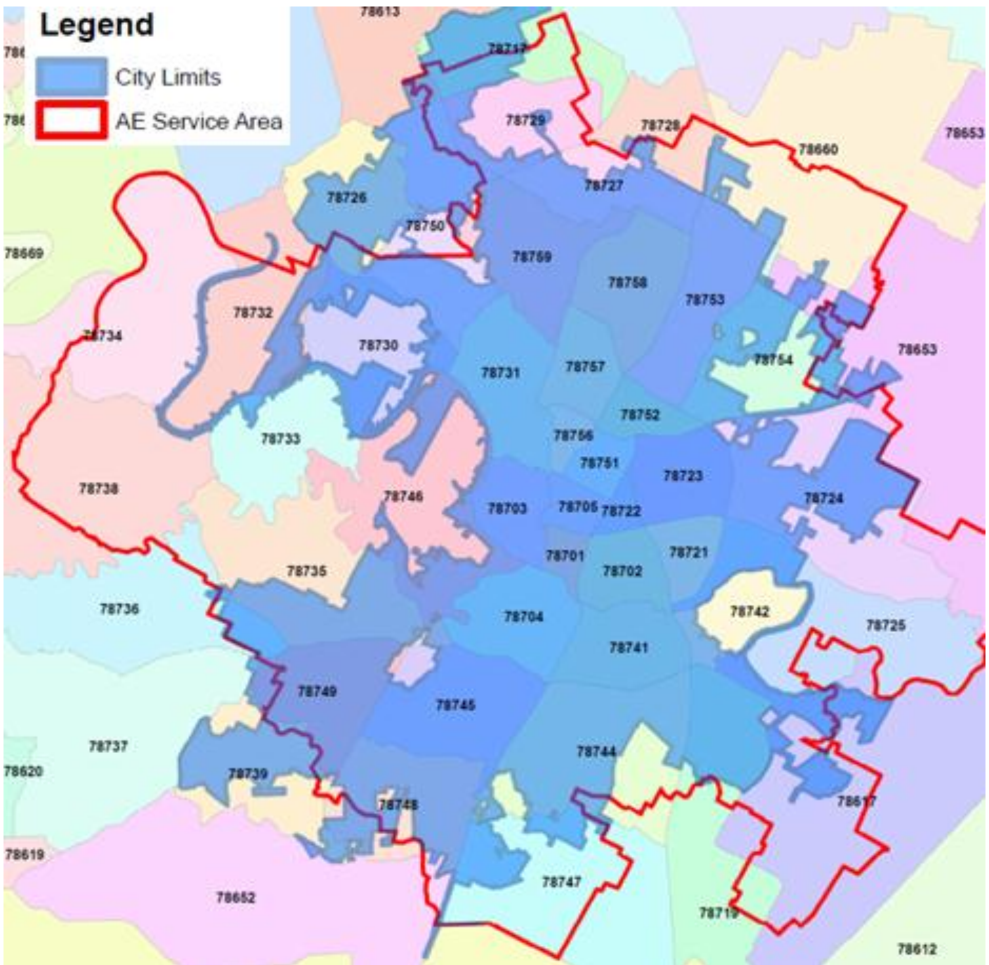

Illustration 1.1 Map of Austin Energy's service area and city limits of Austin

[3] AE Quarterly Report:
http://www.austinenergy.com/about%20us/newsroom/Reports/QuarterlyReportApril2011.pdf

To estimate the solar PV potential in the city, Austin Energy conducted a study in association with Clean Energy Associates. The study surveyed buildings in different zip codes and used GIS data to estimate the rooftop area in Austin that is suitable for solar PV installation. This study also estimated, based on certain assumptions, the potential capacity in MW and energy generation potential in MWh for different building types (Wiese, Libby, Long, & Ryan, 2010). The study estimated that the city has rooftop area suitable for PV deployment to the amount of 66 million square feet on residential buildings and 38 million square feet on commercial buildings. The estimates in terms of total potential capacity in the city (in MW DC under Standard Test Conditions-STC) range from 1420 MW to 2446 MW[4]. Austin Energy also commissioned two studies to evaluate the benefits of solar photovoltaics to the city. One study was aimed at estimating the benefits of solar PV installation and manufacturing in terms of economic development to the city. The other study was aimed at quantifying the comprehensive value of distributed solar photovoltaics to Austin Energy. Both the studies were completed in 2006 and reports published by third party consultants. According to the study conducted by Clean Power Research LLC[5], the value of 15MW of distributed solar PV to Austin Energy in 2006 lies between $2000-$2900/kW of installed capacity depending on the orientation of the systems installed.

Austin Energy set up the Solar rebate program in 2004 with a budget of $933,000 for the fiscal year. Austin's PV rebate program budget is assessed on a year to year rolling basis by the city council for each fiscal year in October with the historical budget allocations shown in Table 1.2.

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[4] Rooftop potential report available at: http://www.ases.org/papers/134.pdf

[5] Report is available at: http://www.austinenergy.com/about%20us/newsroom/Reports/PV-ValueReport.pdf

Year	Budget for solar PV rebates
2004	$933,000
2005	$2,000,000
2006	$3,000,000
2007	$3,180,000
2008	$3,000,000
2009	$4,500 ,000
2010	$4,000,000

Table 1.2: City of Austin approved annual budget for solar PV rebates

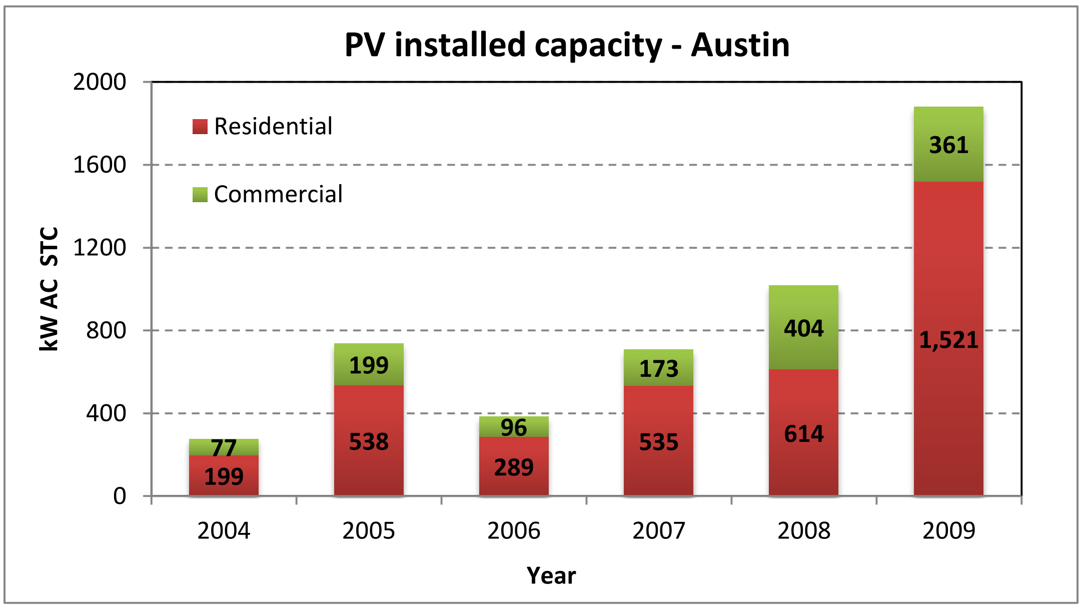

Figure 1.1: Installed capacity of customer sited solar photovoltaics – residential and commercial systems, in Austin from 2004 to 2009

Austin Energy provides rebates for solar PV installations for both residential and commercial buildings within its service territory. The renewable energy credits (RECs) for the power generated are transferred to Austin Energy as part of the rebate contract. The annual installed capacity of rooftop PV in Austin is shown in Figure 1.1. In addition to the rebates, Austin Energy also uses net energy metering mechanism for calculating monthly electricity bills, which charges the customer for only the net energy drawn from the grid. Using two way meters, customers in AE service territory get credited at the retail rate for any excess energy exported to the grid. A more detailed description of net metering practices and billing calculations is presented in chapter 6.

1.2 Motivation For Study

The PV rebate program has funded more than 1000 residential and 100 commercial installations till date. These rebates combined with federal tax credits and savings in energy costs have been the drivers behind growth in customer sited PV capacity. Incentive programs for low carbon energy technologies are designed to support innovation and technology diffusion that is expected to eventually lead to lower costs. The high upfront cost of installing a PV system is currently a barrier to the diffusion of the technology. The cost of installing PV capacity varies with a number of factors viz. module costs, type of installation (new home or retrofit), installer experience etc. With millions of dollars invested in providing incentives for adoption of solar PV, there is an interest in tracking the progress of adoption. Thus, analyzing cost and adoption trends in PV installations would help identify the factors that affect pre-rebate system costs. It also helps in evaluating the progress of the program so far and in setting future targets.

Although the module prices are set at the global level (local supply and tax rates may have a minor effect), the rest of the cost of installing a PV system (called Balance of System –BOS costs) are a function of the maturity of the local market. In particular, it depends on the installer experience, cost of auxiliary electrical equipment and the competition level among installers. Thus, it is important to study and analyze the trends in costs and capacity at the local level to focus on progress in local infrastructure that is in place for supporting the growth of PV.

To advance this data analysis with a more sophisticated methodology, I have also used technology diffusion modeling to statistically model the adoption of solar PV in Austin. These models are based on the hypothesis that technological innovations are adopted by consumers based on communication with people who have already adopted them. The timing of adoption depends on the type of consumer (innovator, early adopter, late adopter etc.), the benefits of technology in consideration and other marketing variables like price.

Modeling the rate of adoption with a diffusion model would help in comparing the progress with other similar innovations as well as in forecasting the probable future path of adoption. Diffusion models applied to solar PV, but in different geographic locations would also let us compare the local effects and that of different policy actions in these areas. Some of the more commonly used technology diffusion models include Logistic growth models, Gompertz curves and the Bass model for technology diffusion (also called the mixed source information model, because it considers the effect of both a common source of information as well as the effect of communication networks) (Bass, 1969 & Geroski,2000). The Bass model and its variants have been very extensively used to estimate the rate of diffusion of many technologies. A more detailed description of the theory of technology diffusion and different models of adoption is presented in chapter 3.

The third part of the thesis studies the net metering mechanism used by Austin Energy. Net metering, the current billing mechanism for Austin Energy customers with solar PV installations, charges the customer for only the net energy drawn from the utility. The distribution service charge is also calculated based on the net energy consumed, but not the actual grid usage. A customer with a solar PV system draws energy from the grid when the system produces less than what is actually being consumed, usually during the night. During the day, if the PV system generates more electricity than the actual energy consumption, the system exports excess energy into the grid (the net meter reads negative). During both these periods, the utility is providing the distribution service to the customer, but is charging the customer only for the net electricity drawn from the grid. Under low penetration of distributed generation, this might constitute a minimal revenue loss. However, under higher penetration of solar PVs, this might be a significant source of revenue loss for the distribution utility. I analyzed an alternative tariff mechanism that considers the actual grid usage instead of the net energy drawn in a billing period.

1.3 Research Goals

This thesis is an attempt to understand and describe the diffusion of solar PV systems in the city of Austin; the role of incentives in promoting diffusion and an analysis of net metering billing mechanism and the impact on distribution rates under higher penetration of distributed generation (focus on solar PV) in the city.

The first goal of the thesis is to study the data on installed systems, construct descriptive statistics and try to interpret the trends in costs, capacity and incentives. Using these descriptive statistics, I attempted to analyze and explain the features of Austin's solar rebate program. The second goal was to model the growth in customer sited solar PV systems using diffusion theory to try and estimate the probable future path of adoption. The third goal is a 'what-if' type of study on one of the expected changes to a utility revenue stream under high penetration of distributed generation. First, I model the actual usage of the distribution grid by a PV system owner, as against the existing practice of measuring only the net energy drawn from the grid. Then, I estimate the change in distribution service revenues for the utility under the current and alternative net metering system.

1.4 Structure Of The Thesis

The thesis is divided into 6 chapters. In the following chapter, a summary of data and descriptive statistics is presented, and an effort is made to draw interpretations from these trends. In chapter 3, a literature survey and background material on technology diffusion theory and modeling is presented. In chapter 4, the assumptions and modeling methodology for Austin's solar PV diffusion is explained and results of the model are presented. In chapter 5, I present the current net metering mechanism and calculate the changes in an alternative tariff structure and chapter 6 concludes the thesis with suggested areas for further research.

Chapter 2: Trends and Statistics

This chapter focuses on analyzing descriptive trends in the underlying data on the growth of solar photovoltaic installations in the city of Austin. This is accomplished by summarizing the data in tabular and graphical form. The data for national level statistics is obtained from Lawrence Berkeley National Laboratory (LBNL)[6]. The initial section presents trends in installed capacity and costs, and the following sections present trends in incentive levels and net cost to the customer.

The original dataset from Austin Energy contained three sets of data: ‘residential’, ‘commercial’ and ‘residential with energy efficiency’. The residential set contained data about all the PV systems that were installed on individual households from 2004, when the rebate program started till the end of 2009. The ‘residential with energy efficiency’ dataset contained data on systems that were installed on individual households after the energy efficiency requirements came into place in 2009. The commercial dataset contained data on all the systems installed on commercial buildings from 2004 to 2009.

The datasets contained information on the technical characteristics of the system installed (PV module model, inverter model and efficiency, tilt and azimuth of the roof, capacity in DC and AC under STC conditions), important dates for each system (application, preliminary survey, approval, final inspection), the total installed cost and the final rebate amount awarded.

2.1 Data Conventions

In this thesis, the focus is on the *installed cost* of a solar PV system. This refers to the cost per unit capacity to the owner of installing a photovoltaic system prior to any

[6] LBNL published a series of reports named ‘Tracking the Sun’ that track the trends in installed costs of customer sited PV systems on a national level.

incentives. The unit of measurement of installed cost is dollars per watt ($/W AC STC). The 'AC STC' refers to the power output in alternating current under standard test conditions.[7] The installed costs are adjusted for inflation and calculated in standard 2010 dollars by using annual CPI data.

Data points with missing entries and partially incomplete information, especially entries without data on costs, installed rating, and inverter efficiencies were removed from the dataset. However, for estimating the capacity trends as well as rates of diffusion accurately, all possible data points with information on capacity were included. So entries that had information on the system rating, but not the installed costs were still used to calculate the trends in capacity, but the average cost calculations were made by excluding these data points. Similarly, outliers in cost data were excluded in average cost calculations, but were included in capacity estimates. Table A.1 in Appendix A includes the table with statistics on raw data, and the cleaned data.

2.2 Austin Energy's Solar Rebate Program-Basics

Austin Energy (AE) provides capacity based upfront rebates for residential solar PV installations. AE also provided capacity based rebates for commercial installations until 2009, when the program changed to a performance based incentive (PBI). In 2009, AE introduced minimum energy efficiency requirements for properties to be eligible for residential rebates. The eligible module and inverter models are the same as that of the California Solar Initiative. The system needs to be installed by a registered contractor from a list posted on AE's website. For residential systems, the rebate amount is capped

[7]Other rating conventions are also used in literature: permutations of AC or DC power output measured under either the standard test conditions (STC) or under PVUSA test conditions (PTC). The most commonly used convention is DC watts (module nameplate rating) at STC. Since information on inverter efficiency for each system installed in Austin is available, I included the derate factor to calculate AC watts.

at \$15000 per year and at \$50000 for lifetime. The rebate amount started at about \$5/kW and is currently at \$2.5/kW. Historical rebate levels are shown in Table 2.1[8]. The rebate amount is calculated based on kW of AC capacity at STC. The formula is:

$$Rebate = [No.of\ modules] \times [Rating\ per\ module(DC\ Watts\ STC)] \times [Inverter\ efficiency] \times [Rebate\ level]$$

The current PBI for commercial systems pays the customer based on the yearly performance of the system. The current rate is \$0.14/kWh generated by the system[9]. The term for payments is limited to 10 years. Only system sizes below 20 kW are currently eligible for the PBI payments. Under the terms of the contract, all the renewable energy credits generated by the system are transferred to Austin Energy.

Year	**Rebate Level ($/Watt AC STC)**
2004	$5.00
2005	$4.50
2006	$4.00 - $4.50
2007	$4.50
2008	$4.50
2009	$4.50 - $3.75
2010-11	$2.50

Table 2.1 Capacity based rebate level for PV systems (on a $ per Watt scale) from 2004 to 2010 in Austin Energy's solar rebate program

8 Source: Austin Energy Solar Programs Presentation, February 23, 2011 by Leslie Libby

9 For more information on AE's solar rebates, please go to: http://www.austinenergy.com/Energy%20Efficiency/Programs/Rebates/solar%20rebates/index.htm

2.3 Trends in Capacity and Costs

2.3.1 Capacity trends

The data on residential photovoltaic installations runs from 2004 to 2010. Figure 2.1(a) shows the annual trend in the number of residential systems installed in terms of frequency distribution in the dataset and Figure 2.1(b) shows the trend in terms of the actual number of systems and installed capacity, measured in kW AC measured under standard test conditions (STC).

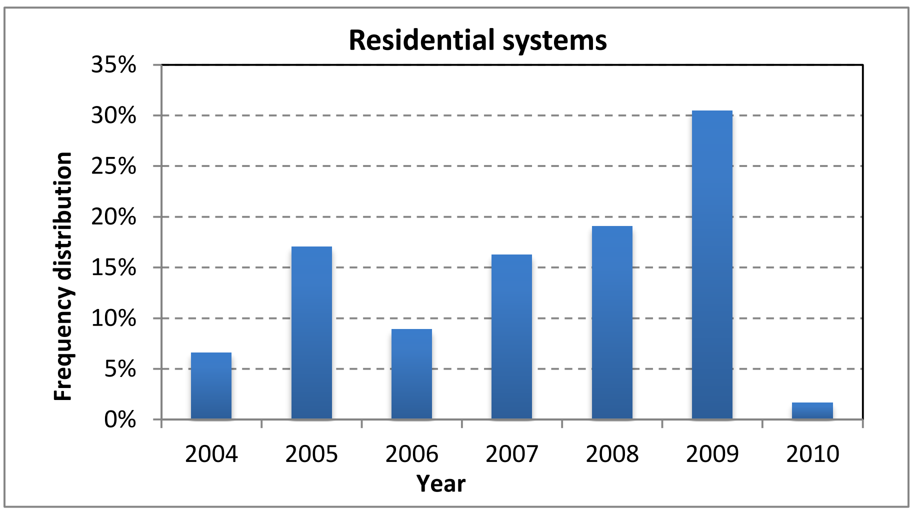

Figure 2.1(a) Frequency distribution of residential solar PV systems in Austin showing the percentage of systems in the dataset installed each year[10].

As can be seen from the figure 2.1(a), the data is skewed towards the later years, as more and more systems were installed in 2008 and 2009. As of early 2010, when this dataset was generated, more than 30% of the residential systems in AE's service area were installed in 2009 and close to 50% were installed in 2008 and 2009. The residential installed capacity more than doubled in 2009 (1521 kW) compared to the 2008 figures (614 kW). The data for 2010 is incomplete, and therefore shows a much smaller number

[10] The data for systems installed in 2010 is incomplete, hence the low numbers.

for the installed capacity. The data set used to plot Figures 2.1 and 2.2 is included in Appendix A (Tables A.2 and A.3).

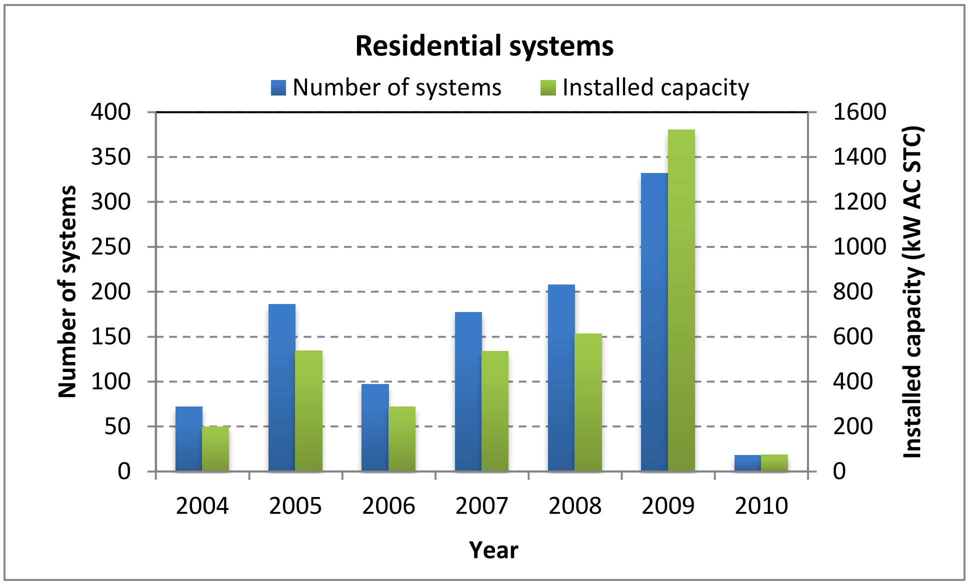

Figure 2.1 (b) Number of systems and annual installed capacity from 2004 to early 2010 by residential customers

In figure 2.1 (b), the relative lengths of the clustered bars in each year gives a rough estimate of the average system size. It is evident from the graph that the relative length of the installed capacity (green) bar (with respect to the blue bar it is clustered with) has remained constant through 2008, but changed in 2009. Using this very approximate analysis, this increase in the relative length in 2009 indicates an increase in the average system size in 2009. The validity of this inference is demonstrated in Section 2.5 when we look at system size trends and distributions.

Figure 2.2(a) and 2.2(b) show the trends in commercial installations in Austin from 2004 to 2009. As figure 2.2(a) indicates, as of early 2010, about 60% of the commercial systems were installed in 2008 and 2009. All of these systems were installed before the change in commercial incentive program and therefore had capacity based rebates from Austin Energy. Figure 2.2 (b) presents the yearly number of installations and capacity additions by commercial customers.

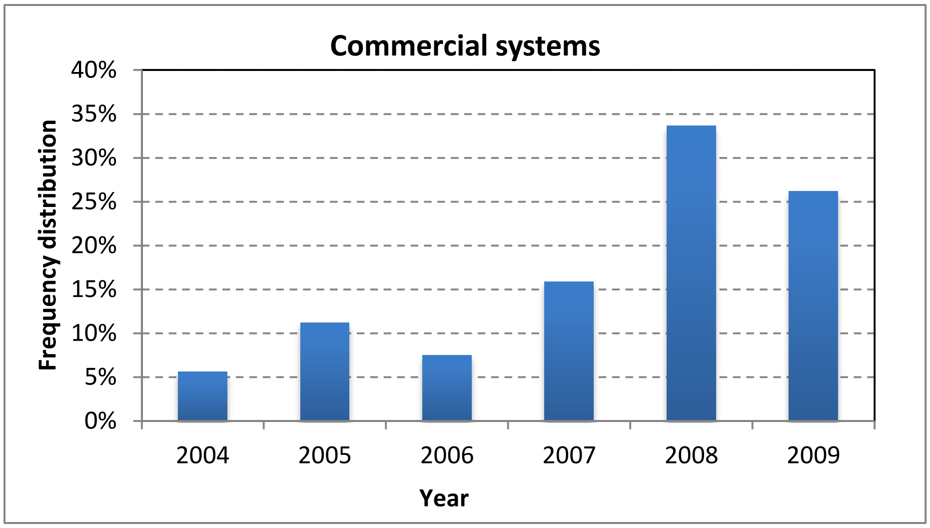

Figure 2.2(a) Frequency distribution of commercial solar PV systems in Austin showing the percentage of systems in the dataset installed in each year.

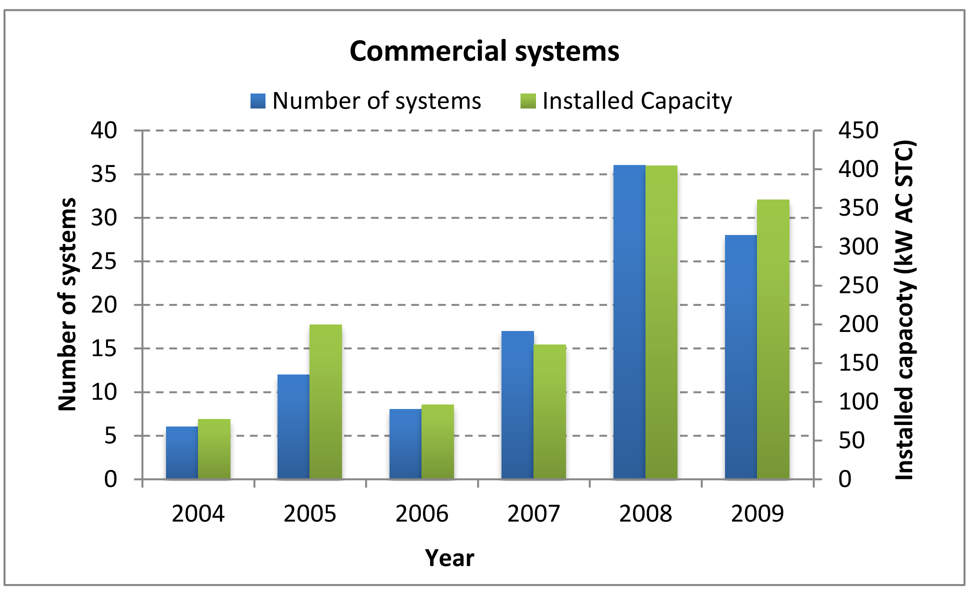

Figure 2.2 (b) Number of systems and annual installed capacity from 2004 to 2009 by commercial customers in Austin

2.3.2Cost trends

Figure 2.3 shows the trend in installed cost in dollars per watt (AC STC) for residential systems. The average cost has remained constant through 2008 and decreased from \$7.87/Watt in 2008 to \$6.62/Watt in 2009. The 'n' values below the horizontal axis in the figure show the number of observations (systems installed) in each year. The error bars show the standard deviation of the installed cost.

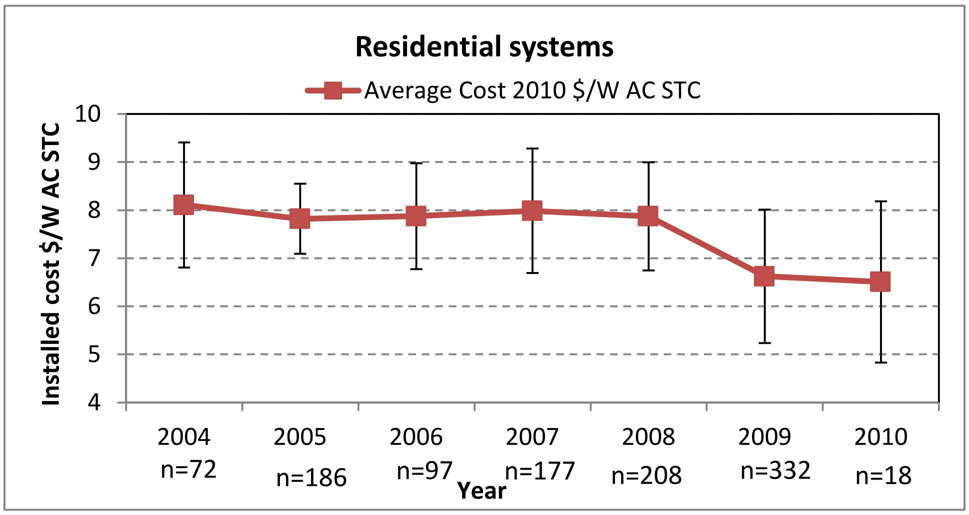

Figure 2.3 Average installed cost with standard deviation for residential PV systems in Austin from 2004 to 2009

Figure 2.4 shows the trend in average system size along with the trend in average installed cost. The average size has remained constant through 2008 at about 3kW and increased in 2009 to about 4.5 kW. The decrease in installed cost of the system coincides with the increase in average system size as shown in Figure 2.4. This is expected since the labor and installation costs (total installed cost less the equipment cost) are averaged on a larger capacity. However, it should be pointed out that this does not necessarily point to economies of scale, as we are looking at a time series of costs and sizes and the increase in size may as well be the result of decrease in prices and not the other way around. Also, about 40% of the installed cost is module price component[11], which is set on a global scale and the overall trend in costs may be influenced by module price trend. The data table used to plot figures 2.3 and 2.4 is given in Appendix A (Table A.3)

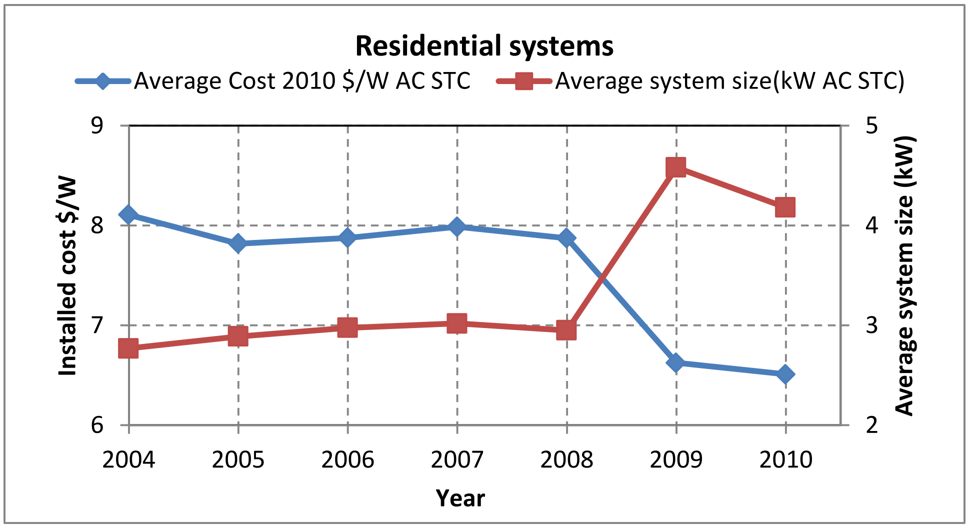

Figure 2.4 Installed cost and average system size of residential PV systems in Austin from 2004 to 2010

Figure 2.5 shows the trends in cost and system size for systems installed by commercial customers. In contrast to figure 2.4, the inverse correlation between cost and size is not directly evident. However, an increase in average system size is coincident with reduction in average cost from 2005-2006 and from 2008-2009. In conversation with a program manager from Austin Energy, we learnt that one of the reasons for this pattern (or lack of it) might be the increase in installed cost for some commercial systems because of including batteries for backup[12]. Also, there are fewer data points in the commercial systems data and therefore, the average cost is highly sensitive to extreme values. Residential systems are usually just grid interface systems without battery

[11] Cite BoS report, RMI

[12] It might also just be a consequence of fewer data points used to calculate the averages in this case.

backup, and the average cost data there reflects the sum of module and balance of system costs only (without batteries).

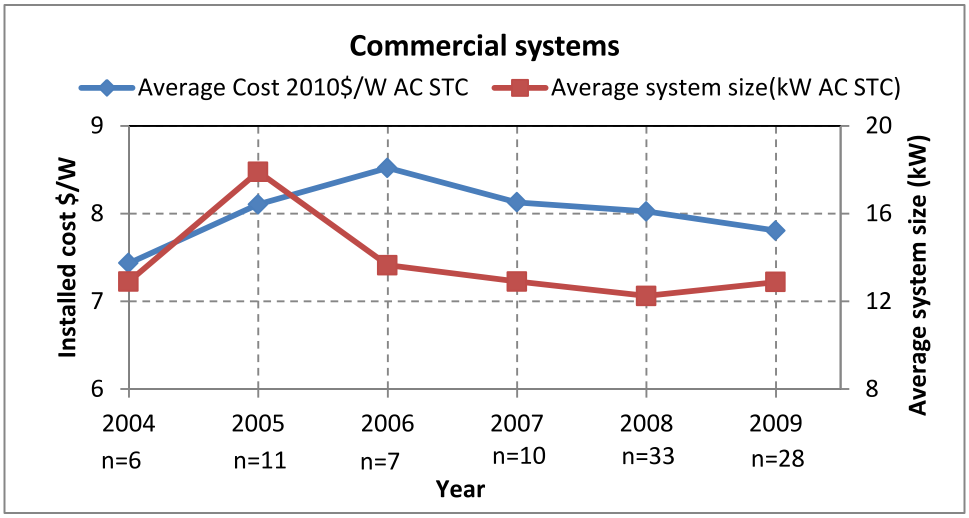

Figure 2.5 Installed cost and average system size of commercial PV systems in Austin from 2004 to 2009

In order to closely look at the trend in installed cost for various system sizes, I plotted the average installed cost with time for different system sizes. As Figure 2.6 indicates, all the size ranges, with the exception of '> 16' have seen an overall decrease in installed costs from 2004 to 2009. However, systems of greater than 16kW capacity have not observed significant decrease in costs. Figure 2.6 also indicates that in all the years except 2005, systems of size less than 2 kW had the highest dollar per Watt cost. The data used to plot figure 2.6 is given in Appendix A (Table A.5).

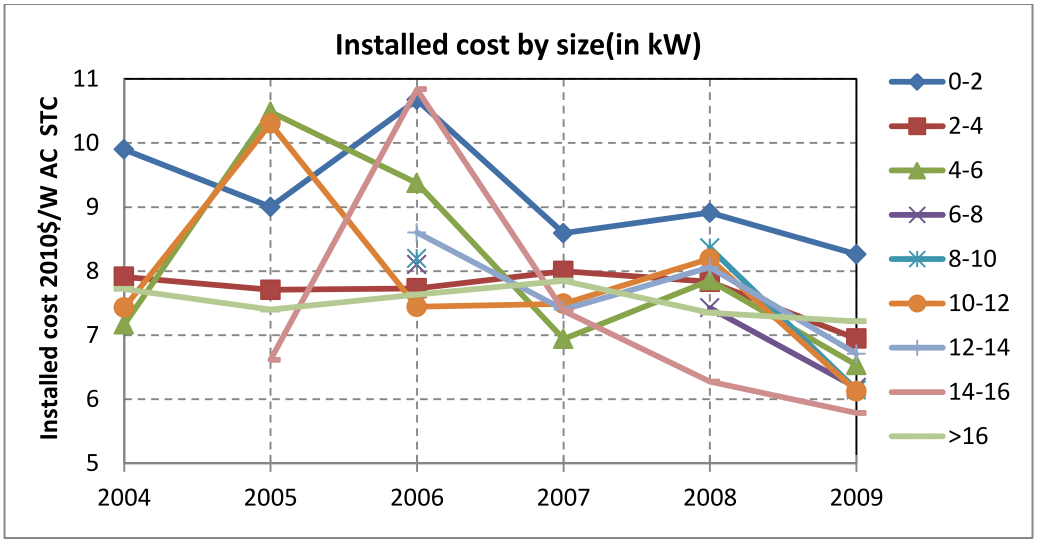

Figure 2.6 Trend in installed cost for different system size categories in Austin from 2004 to 2009

2.4 Economies of Scale

Larger system sizes may reduce the average installed cost with the benefit of economies of scale. This is an expected outcome because with larger systems, the fixed Balance of System costs are spread out over larger installed capacity. Figure 2.7 shows a snapshot (cross section) of installed costs for various system sizes in 2009. It indicates the economies of scale realized with increased system size. The highest average cost was for systems of less than 2 kW (AC STC) capacity at \$8.26/W in 2010 dollars. The average cost decreases to \$6.12/W for systems of 10-12kW size. The decrease in costs from \$7.87/Watt in 2008 to \$6.62/Watt in 2009 may partially be explained by the combination of system size increase as well as the benefit of economies of scale exhibited in 2009.

Figure 2.7 also indicates that economies of scale are not present through the higher system size ranges. Scale effects disappear for systems of greater than 12 kW capacity, which may indicate that economies of scale are overtaken by project specific costs associated with larger systems. Lawrence Berkeley Lab's report tracking solar trends on a national scale suggests that this maybe due to lower level of standardization and increased permitting costs associated with larger systems (Barbose, Darghouth, & Wiser, 2010). The data used to plot Figure 2.7 can be found in Appendix A (Table A.6).

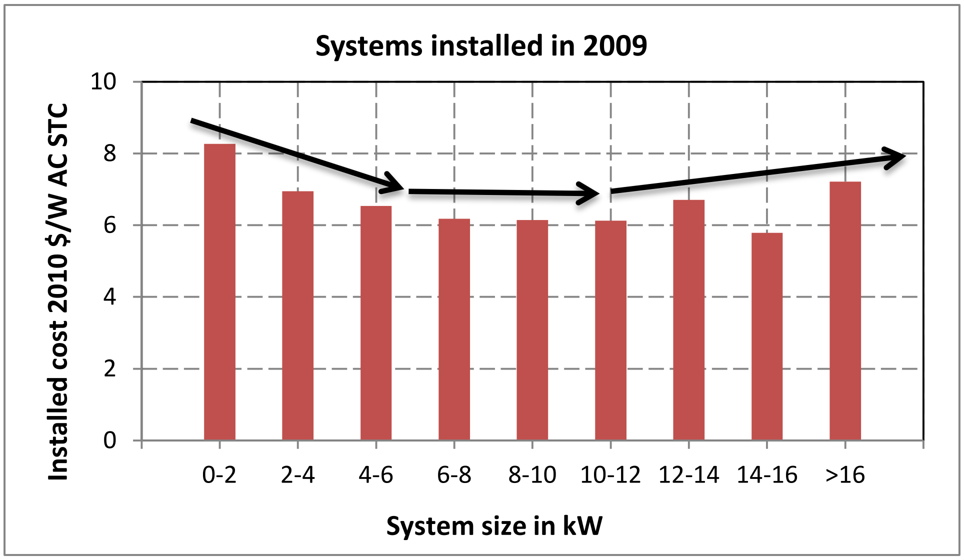

Figure 2.7 Installed cost with size for all PV systems in Austin (residential and commercial) in 2009

2.5 Distribution of costs and capacity

In section 2.3 we looked at the trends in average system sizes for both residential and commercial installations. To get a more complete picture on system sizes, instead of looking at just one value (the average size), we can look at the distribution of sizes in each of these years. This can be done by plotting the frequency distribution of systems in each year into capacity bins (0-2 kW, 2-4 kW etc) as shown in Figure 2.8. It shows the percentage of systems in each size range for each year from 2004 to 2010 for residential systems.

The peak of the distribution curve points to the size range in which most of the installed systems lie in a particular year. As the very narrow distributions from 2004 to 2008 indicate, more than 90% of the systems from 2004 to 2008 were in the 2-4kW size range. The different colored lines from 2004-2008 are not distinctly visible in the graph because of the very similar distribution. However, in 2009, only 52% of the systems were in the 2-4 kW capacity bin, with 21% in the 4-6 kW range and 15% in the 6-8 kW range. The chart shows that the peak is shifting towards higher system size which indicates the average system size for a residential system is increasing with time. With the limited data in 2010, the peak actually shifted to the 4-6 kW bin with 39% of the systems and only 33% of systems were in the 2- 4 kW range. The data used to plot figure 2.8 is given in Table A.7.

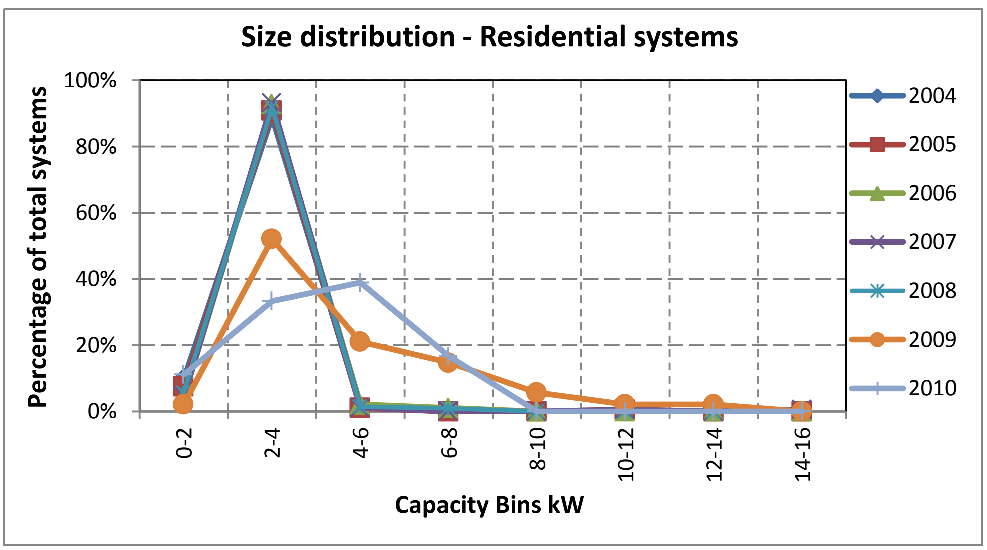

Figure 2.8 Size distribution of residential systems (percentage of number of systems in each size bin) from 2004-2010

A similar type of plot for commercial systems revealed no particular pattern or distribution because of very few observations (95) in total. When categorized according to the year and capacity bins, there were very few observations left in each bin to get any meaningful frequency distribution.

Another statistic of interest is the distribution of costs. The average values presented earlier in section 2.3 is a representative value of the cost, but to get a more complete picture, it helps to look at the distribution of dollar per watt installed cost from 2004-2010.

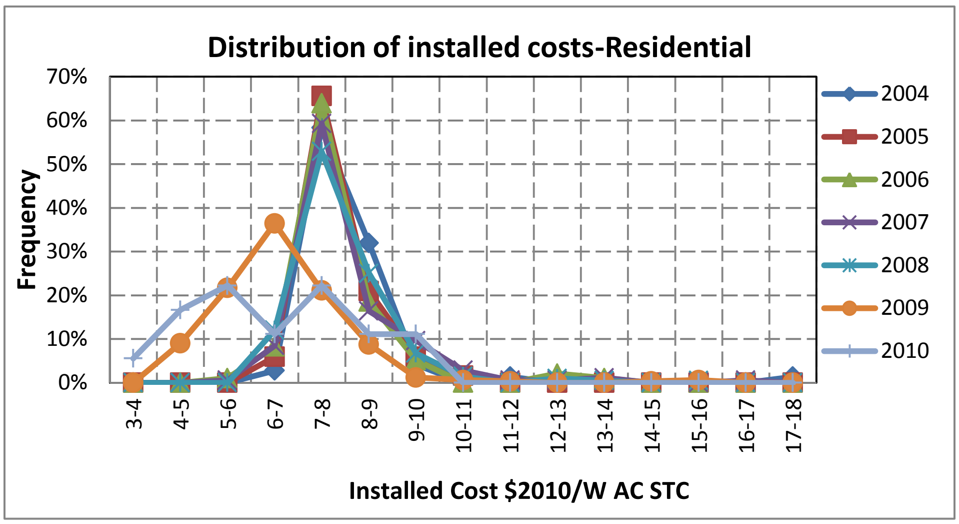

Figure 2.9 Distribution of installed costs for residential systems (percentage of systems in each installed cost bin for each specific year) from 2004 - 2010

Figure 2.9 shows the distribution of residential PV systems with installed cost bins from 2004 to 2010. Each data point shows the percentage of systems in that year with installed costs within the cost bin on x-axis. The peak for a given year represents the cost range in which most of the systems lie in. For example in 2005, about 65% of the installed residential systems have average installed cost between $7-8/W and 21% systems had installed costs between 8 and 9 dollars per watt. Similar to figure 2.8 with the size distribution, the cost distribution also remains narrow from 2004-2008 with most systems having installed costs between $7-8/W. However, the frequency of systems in this bin decreased from 65% in 2005 to 52% in 2008. In 2009, the peak shifted to a lower cost bin, with 36% of the systems having installed costs between \$6-7/kW, and 21% each in \$5-6/W and \$7-8/W. With time, one can observe that the peak of the distribution is shifting towards left side on the horizontal axis. This trend of the peak shifting towards lower cost bins indicates a decrease in installed costs, by allowing us to look at the entire distribution of costs instead of just the calculated average value for a year. The data used to plot figure 2.9 is given in Table A.8.

2.6 Rebates, Tax Credits and Net costs

Financial incentives from federal, state and local governments have been crucial to the growth in adoption of solar photovoltaics. The high cost of installation is a barrier to market penetration of this technology and the rebates lower the net cost to the customer, thereby encouraging adoption of solar PV. PV incentives are usually in the form of feed in tariffs, capacity based upfront rebates, tax credits, renewable energy credits and performance based incentives. There are also indirect benefits through net metering structure, and property tax exemptions.

Austin Energy offers capacity based rebates for residential customers and performance based incentives[13] for customers in the commercial rate class for installing rooftop solar PV. The terms and features of the rebate program are briefly described in section 2.2. Table 2.1 shows the dollar per watt rebate amounts offered by Austin Energy from 2004-2009. In this section, we calculate the rebates offered to customers, federal tax credits and estimate the net cost to the customer. I do not consider the benefits of solar PV, or energy bill savings or perform a levelized cost analysis, but specifically focus on AE rebates and federal tax credits.

[13] Until 2009, commercial customers also received capacity based upfront rebates

Figure 2.11 plots the average installed cost of residential systems by splitting it into three components: AE rebate, federal tax credit and the net cost to the customer. In 2004, the rebate level is at 5.70 in 2010 dollars, the actual rate in 2004 dollars is 5 per Watt. The difference in rebate levels reflects the level of rebate during that year as well as the CPI (Consumer Price Index) conversion factor used to convert into 2010 dollars. Appendix B contains data on the CPI values used. The rebate level in 2010 is less than half the level in 2004, when the program started. There was a cap on the rebate not to exceed 80% of the total installation cost for a project. The rebate amounts shown in figures 2.11 and 2.12 are based on the actual amounts paid. Since the annual revisions apply to fiscal year (Oct-Sep), the average calculated is a little different from the rebate level for any particular year. The tax credits are assessed based on the date when the system is connected to the grid and the proxy we used for this is the date of final inspection by the utility.

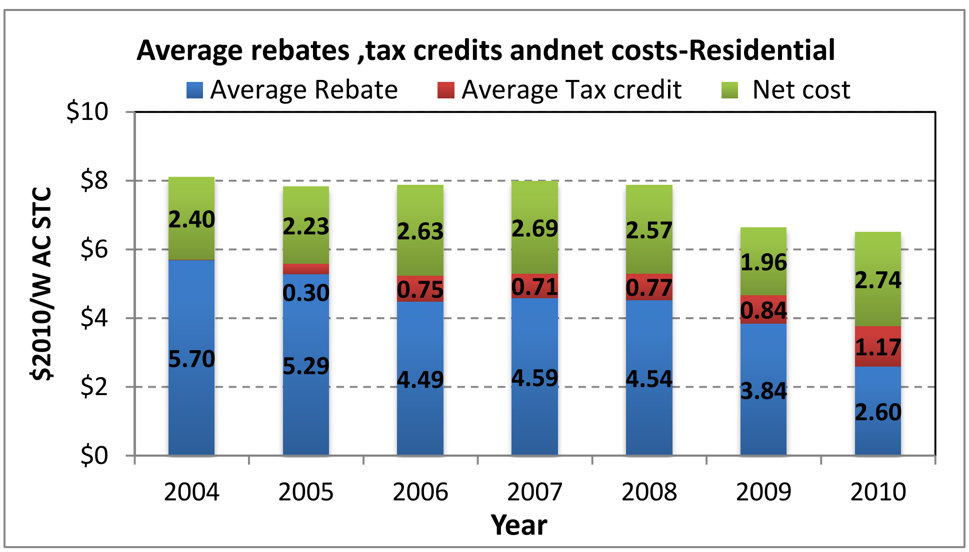

Figure 2.11 Installed cost split into rebate, tax credit and net cost to customer for residential systems from 2004 to 2010

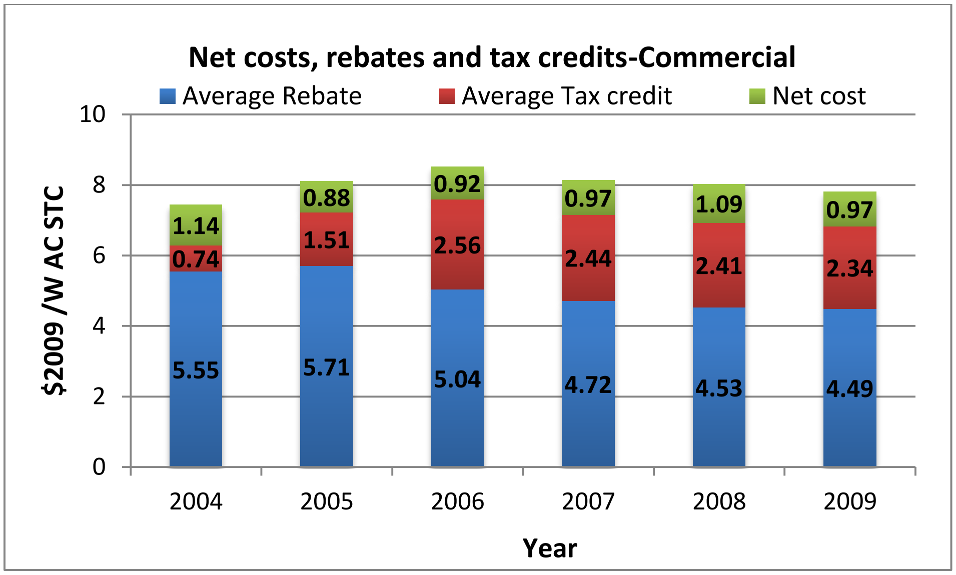

Figure 2.12 Installed cost split into rebate, tax credit and net cost to customer for commercial systems in Austin from 2004 to 2009

Figure 2.12 shows the rebates, investment tax credits and net cost for commercial rate class customers. One can observe that the federal tax credit as a fraction of the installed cost is higher for commercial systems compared to residential systems (tax credits for residential systems started in 2006). Residential personal tax credit had a cap of $2000 until the end of 2008, and commercial systems had no cap on the Investment tax credit, which partially explains the higher tax credit for commercial systems. Also, the cost basis used for calculating the tax credit is higher for commercial systems because it is based on the total installed cost. For residential systems, the 30% tax credit was calculated based on the total installed cost less the utility rebate. This also explains why the tax credit is lower for residential systems even after the $2000 cap was removed in 2009. Further details on the assumptions and equations for tax credit calculations are given in Appendix B.

Chapter 3: Technology Diffusion-Literature Review

Technology diffusion has been area of research since many decades. The interest in trying to explain why certain innovations are adopted and the rate at which they are adopted existed long before any analytical models have been proposed to model the behavior. This chapter reviews the literature on innovation and technology diffusion, and presents different models that have been proposed to explain the diffusion of new products. The most popular text on technology diffusion is by Everett Rogers, where the author presents the different elements of diffusion of innovations in a qualitative manner. The following section (3.1) reviews the theoretical principles that govern the adoption of innovations as described by Rogers. In section 3.2, I present some of the analytical models that have been proposed to model the penetration of new technologies. In section 3.3, I present a variation of the Bass model that we use in this thesis to model the diffusion of solar PV in the city of Austin.

3.1 Adoption of Innovations-Rogers

Everett Rogers in his book titled 'Diffusion of Innovations' defines diffusion as "the process in which an innovation is communicated through certain channels over time among the members of a social system". It includes both the planned and the spontaneous spread of new ideas. He defines the four elements of diffusion as (1) the innovation, (2) communication channels, (3) time and (4) the social system. All these elements play a key role in the result of whether or not an innovation sustains adoption or fizzles out.

In this section, we focus on explaining the relationship between the parameters that characterize these elements of diffusion and in the following section, we present analytical formulations that model the process of diffusion. In particular we seek to explain the rate of adoption of an innovation based on the existing communication channels and the innovativeness of the social system. This theory is the foundation for most of the diffusion models in use for technology forecasting.

Rogers proposes a classification framework of population in a society into adopter categories, based on when they first begin using the innovation. He uses the timeline of the diffusion process of an innovation to classify the people who have adopted it based on their relative position in the technology S-curve. It has been demonstrated, for many innovations, that plotting the cumulative number of people (or any other metric used for adoption) who have adopted an innovation with time results in an S-shaped curve (similar to the cumulative distribution function of a normal random variable).

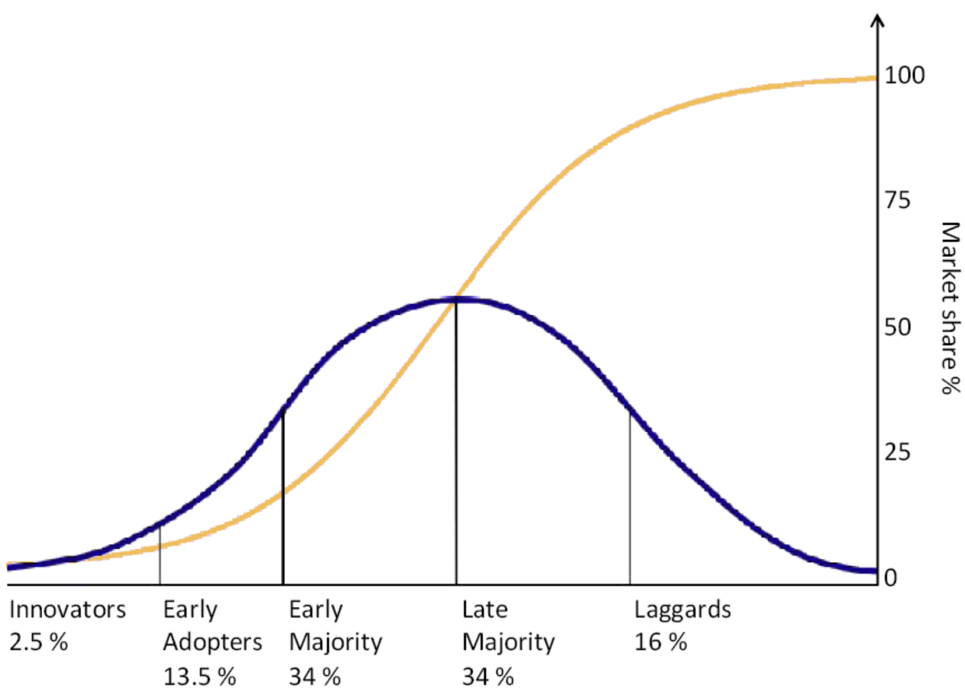

Illustration 3.1 Adopter categories and the diffusion S-curve

Based on the position on the normal curve, adopters can be categorized into five mutually exclusive groups as:

i. Innovators –the first 2.5% of the population in a system (they lie approximately to the left of the point that designates the mean minus 2 standard deviations).

ii. Early adopters –the next 13.5% to adopt the new idea (they lie in the area bound by the mean minus 2 standard deviations and mean minus one standard deviation)

iii. Early majority – the next 34% of the adopters (they lie between the mean date of adoption and mean minus one standard deviation).

iv. Late majority – the next 34% to adopt the idea (lie between the mean and mean plus one standard deviation)

v. Laggards – the last 16% to adopt the innovation

The path of diffusion for any technology is unique to the characteristics of the technology and the social system in which it is introduced. The timeline of adoption is quicker or slower based on these characteristics. In the initial period, the innovativeness of an adopter is the key driver for the initial market penetration, and with time, the effect of communication networks becomes the important driver for a product.

3.2 Modeling Technology Adoption

A number of models have been proposed to explain the adoption of a new product in the market in marketing literature. Most of the models are variations of the logistic growth model that has been widely used to explain the population dynamics in biological growth. Most of these models result in an S-shaped curve when market share (or any other metric of cumulative adoption) is plotted against time. Tsoularis contains an excellent review of the variations of a generalized logistic growth equation along with examples of applications in a variety of fields (Tsoularis, 2001). Geroski reviews logistic models and variations used to study technology diffusion (Geroski, 2000).

3.2.1 Early models of technology diffusion

Edwin Mansfield proposed one of the earliest models for adoption of new technologies (Mansfield, 1961). He used a logistic equation to model the number of firms adopting a new technology as a function of time. He used his model to estimate the rate of imitation of twelve new innovations.

Another example is the simple substitution model proposed by Fisher and Pry (1971). They have adopted the logistic growth equation to successfully model the adoption rates of many products and technologies. The Fisher-Pry model is based on the hypothesis that the adoption curve is characterized by the early growth rate parameter (α) and the time at which adoption is half complete (t_0). Their equation is written as:

$$\frac{f}{1-f} = \exp[2\alpha(t - t_0)] \qquad (3.1)$$

where 'f' is the fraction of the market share of a new product and 't' is time. Note that when $t = t_0,\ f = 0.5$.

Another class of models uses the hazard function approach to derive variations of the logistic growth equation. One of the most popular in marketing literature is the Bass model proposed first by Frank Bass in 1969 (Bass, 1969). The Bass model proposes a functional form for the hazard rate in the case of new product diffusion. Hazard rate is defined as the probability of an event occurring at time 'T', conditional on the event not happening up to time 'T'. If $f(T)$ is the probability density function of an event, and $F(T) = \int_0^T f(t)dt$ is the cumulative distribution function, then the hazard rate at 'T' is defined as

$$P(T) = \frac{f(T)}{1 - F(T)} \tag{3.2}$$

In the context of diffusion theory, the event is the purchase of a new product or technology. So *P(T)* is defined as the probability that a purchase is made at time T given that no purchase has been made yet. Bass proposed that this probability is an affine function of the total number of purchases made until time 't'.

$$\frac{f(t)}{1 - F(t)} = P(t) = p + \left(\frac{q}{m}\right) Y(t) \tag{3.3}$$

where Y(t) = total number of purchasers in the interval (0,t)

m = total number of potential purchasers

p = coefficient of innovation

q = coefficient of imitation

The parameters p and q reflect the impact of innovators and the impact of social networks of communication respectively, in the population. The Bass model states that the probability of purchase of a new product, given that it did not occur yet, is the sum of two effects: (1) the innovative component of the buyer and (2) the effect of communication with the population who have already purchased the product.

Gerosky derives the equations for the epidemic model, mixed information source model and a probit model of technology diffusion, with variations that factor in the heterogeneity in the population that adopts these technologies (Geroski, 2000).

Horsky proposes a model to include the effects of price and income into the Bass diffusion model. He proposes that the potential number of buyers at any time t is a fraction of the maximum potential and that this proportion depends on the 'effective price' of the product. The effective price is a function of the wage, the price and the financial benefit of purchasing the product. The total number of potential purchasers m in the Bass model is now written as $M(t)$, a function of time:

$$M(t) = L(t).S(t) = \frac{L(t)}{1 + exp\left(\frac{-(K + w - k.p)}{\delta}\right)} \tag{3.4}$$

where L(t) = total market potential at time *t*

S(t) = proportion of population who would purchase the product given the wage *w* and market price *p* of the product.

δ - a scaling factor depending on the wage distribution

K, k - parameters of the model to be estimated

3.2.2 Technology diffusion models applied to energy systems

Lund applies the logistic equation to fit diffusion S-curves for 11 technologies in both energy production and energy end use with data from different geographic regions (Lund, 2006). He uses least squares to fit the datasets with assumptions on the maximum potential market share (carrying capacity) of different technologies.

Higgins *et. al.* adopt a variation of the Bass model to study the path of adoption of solar energy technologies (PV and solar water heaters) in the suburbs of Brisbane, Australia (Higgins, Foliente, & McNamara, 2011). They use it as an input for estimating the reduction in greenhouse gas emissions from residential sector under different policy actions. The model is an extension of the basic Bass model that incorporates differences in population characteristics (population growth, income, property values) in the seven suburbs of Brisbane and the effect of cost on the ceiling of adoption. They used the model developed by Horsky to modify the Bass model to include the effects mentioned (Horsky, 1990). Unlike the Bass model, where 'm' the market potential is fixed, the model uses a time varying function for the market potential, $M(t)$. The equation for their model is:

$$A'(t) = \frac{dA(t)}{dt} = \left(p + \frac{q}{M(t)}A(t)\right).(M(t) - A(t)) \tag{3.5}$$

where $A(t)$ – level of adoption at time t

$A'(t)$ – change in adoption at time t

p, q – coefficients of innovation and imitation from the Bass model

$M(t)$ – ceiling of adoption at t that depends on the actual population and other characteristics.

Bollinger *et. al.* model the diffusion of solar PV in California on a temporal and spatial scale and explore the pattern of geographic clustering (Bollinger & Gillingham, 2010). They examine the role of environmental preferences and peer effects as the cause of these clusters of adoption and perform a zip-code level analysis on the effects of previous adopters on the probability to adoption. They use a hazard model to explain the time between successive adoptions as a function of number of previous adopters, price effects and demographic variables.

Maribu *et. al.* model the diffusion of distribute energy resources (DER) under different regulatory scenarios (Maribu, Firestone, Marnay, & Siddiqui, 2007). They build a bottom-up model to estimate the profitability of adoption of DER technologies and use building floor space with DER as the metric for the level of market penetration.

All the models described above result in the technology diffusion S-curves (or at least initial parts of the curve) for the particular technologies considered. The advantage in using hazard rate based models is that it allows us to model the rate of adoption at an early stage in the product diffusion cycle. With available data and assumptions on market potential and policy scenarios, these models also allow us to forecast possible paths of adoption for these technologies.

3.3 Bass Model - Extensions and Estimation

In this section, I describe the estimation methods first proposed by Bass for his model and subsequent extensions added to include the effect of price and other marketing mix variables. The starting point for these derivations is equation (3.3) introduced earlier. The material in this section is based on continuous and discrete models developed by Bass and the non linear least squares estimation on the continuous form proposed by Jain and Rao (Jain & Rao, 1990).

3.3.1 Continuous form of Bass model

Recall equation 3.3 presented earlier:

$$\frac{f(t)}{1-F(t)} = P(t) = p + \left(\frac{q}{m}\right)Y(t)$$

Note that $Y(t) = \int_0^t S(t)dt$, is the cumulative sales until time *t* where $S(t)$ is the number of purchases (sales) in the interval (*t*, *t*+*dt*). Since f(t) is the probability density function of purchase at time *t*, it follows that sales in time *t*, $S(t) = mf(t)$ (where m=total market potential) and therefore, $Y(t) = \int_0^t mf(t)dt = m\int_0^t f(t)dt = mF(t)$. So equation (3.3) now becomes

$$f(t) = \big(p + qF(t)\big)[1 - F(t)]$$
$$\frac{dF}{dt} = p + (q-p)F - qF^2 \tag{3.6}$$

Equation (3.6) is a first order non-linear differential equation. The solution is:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \tag{3.7}$$

3.3.2 Discrete version of the Bass Model

Bass also formulated a discrete model to estimate the parameters *p* and *q* when the data is in discrete longer time intervals (e.g. annual). The basic equation for sales at time 't' is given by $S(t) = mf(t)$. Now substitute the expression for *f(t)* from the first part of equation (3.6), to get:

$$\begin{aligned} S(t) &= m\frac{d}{dt}F(t) = pm + (q-p)mF(t) - qmF^2(t) \\ S(t) &= \frac{d}{dt}Y(t) = pm + (q-p)Y(t) - \left(\frac{q}{m}\right)Y^2(t) \end{aligned} \tag{3.8}$$

Using discrete time-series data for sales, an approximation for the derivative on the left hand side of equation (3.8) is the difference between the sales in successive times. To be precise, Bass proposed using sales during the period (*t-1*) to *t* instead of *t* to (*t*+*dt*) (discrete approximation of a continuous function) since the data available on sales is usually grouped into time periods like month, quarter or year. Using this approximation, we get:

$$S_t = a + bY_{t-1} + cY_{t-1}^2 \tag{3.9}$$

where S_t = sales during the period from (*t-1*) to *t*.

$Y_{t-1} = \sum_{i=1}^{t-1} S_i$ = cumulative sales till time (*t-1*).

From the estimates of *a*, *b* and *c*, the parameters *p*, *q*, and *m* can be calculated as:

$$m = \frac{-b \pm \sqrt{b^2 - 4ca}}{2c}; q = -mc \; and \; p = {}^{a}/_{m} \tag{3.10}$$

3.3.3 Market potential correction

In a bell shaped curve (like the normal curve for Sales), using the difference approximation underestimates the derivative in the intervals before the peak and overestimates it after the peak (Schmittlein & Mahajan, 1982). Schmittlein and Mahajan use the original differential equation by Bass to come up with a Maximum Likelihood Estimation for p, q and c. They also introduce an eventual probability factor for the ceiling of adoption. The argument is that the CDF is only appropriate for the eventual adopters, and if, for an individual, the probability of eventually adopting is '*c*', then the ceiling of adoption (the total number of people eventually adopting) is actually '*cm*', not the total population *m*. Srinivasan and Mason proposed a Nonlinear Least Squares (NLS) procedure for estimating the model, with similar formulation as Mahajan and Schmittlein including the eventual probability factor (Srinivasan & Mason, 1986). They use the CDF formula as in (3.11) instead of (3.9) and (3.10) used by Bass:

$$P(t) = c[\,F(t) - F(t-1)] = c\left[\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} - \frac{1-e^{-(p+q)(t-1)}}{1+\frac{q}{p}e^{-(p+q)(t-1)}}\right] \qquad (3.11)$$

where P(t) is the probability of adoption in time interval (*t-1*) to *t*.

The conditional probability of adoption in period (*t-1*) to *t* given that the individual did not adopt until time (*t-1*) is given by:

$$CP(t) = \frac{c[F(t) - F(t-1)]}{1 - c.F(t-1)} \qquad (3.12)$$

and the sales in the period (*t-1*) to *t* is given by the probability multiplied by the market potential at time (t-1)

$$S_t = \big(M - X(t-1)\big)\frac{c[F(t) - F(t-1)]}{1 - c.F(t-1)} + \varepsilon_t \qquad (3.13)$$

where X(t-1) is the cumulative sales until time (*t-1*).

In order to include the effect of price on the adoption of durables, Jain and Rao proposed three models that extend the classic Bass model to incorporate the effect of price (Jain & Rao, 1990). In all of their models, price affects the market potential (or ceiling of adoption) M or the factor *c* which denotes the eventual probability of adoption.

The hypothesis is that lowering the price of a product would bring more people into the potential adopters segment. Including price (or other variables) in the model enables us to more accurately estimate the parameters because without these explanatory variables, the effect of p and q may be exaggerated. However, to forecast the adoption of products, using these models would require the knowledge of future price expectations or price forecasts. A model including the price as an explanatory variable is presented in section 4.3.

3.3.4 Peak Adoption Rate

In the plot of sales (or any other adoption metric) vs time, for the proposed normal shaped curve, the sales rate peaks at a certain point in time, and then declines after that. This time T* is when the function f(t) is at maximum. By differentiating the equation for f(t) and setting it to zero, T* can be calculated as:

$$T^* = \frac{1}{(p+q)} \log({}^{q}/_{p}) \tag{3.14}$$

Chapter 4: Model results and Discussion

In this thesis, I have used the data on installations from Austin Energy to model the rate of adoption of solar PV. Because of the wide variation in the size and rating of different solar modules, the number of solar installations might not be the right metric to measure the adoption of solar PV. In place of the number of adoptions, we use the capacity installed in kW during a time interval as the metric for adoption. We use quarterly grouped data from 2004 to 2009 and we restrict the study to residential installations in Austin. Figure (4.1) shows a bar plot of quarterly cumulative installed data

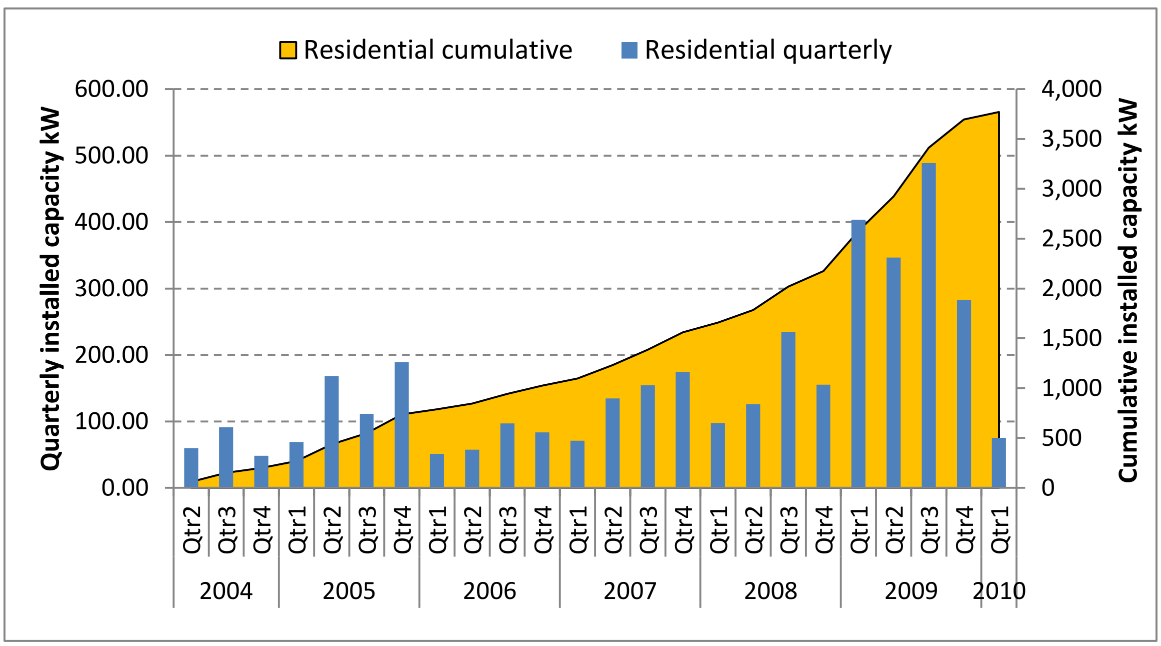

Figure 4.1 Quarterly and cumulative installed capacity for residential customers

The area chart in Figure (4.1) shows the initial stage of the proposed S-curve of cumulative adoption and in the following sections of this chapter, I fit the data different models to estimate the parameters of the curve. First, I used a simple logistic model to fit the data and estimate the parameters associated with the model and used them to construct the S-curve forecast. Then, I used the modified version of the Bass model proposed by Srinivasan and Mason (equation 3.13) to estimate the parameters using Nonlinear Least Squares. In section 4.3, I have modeled the quarterly sales including the installed cost (as a proxy for price) as specified by Jain and Rao. The first and second models can be used to forecast the adoption rate, since they do not have any explanatory variables except the time variable. The third model needs an input for future installed cost in order to be able to forecast the adoption rate. With installed cost forecast not available, we could not make a forecast of adoption rate using the third model.

4.1 Simple Logistic Model

The simple logistic model assumes that the only driver behind adoption is communication between members of a social system. The hypothesis is that the rate of adoption ($^{dX}/_{dt}$) is proportional to the product of the fraction of the maximum potential that has already adopted ($^{X(t)}/_{M}$) and the population that has not yet adopted (M - X(t)).

The simple logistic growth model equation is shown below:

$$\frac{d}{dt}X(t) = r\left(\frac{X(t)}{M}\right)(M - X(t)) \tag{4.1}$$

where X(t) is the cumulative adoption at time ‘t’

r is a positive parameter in the logistic model (penetration rate)

M – Ceiling of adoption (or maximum carrying capacity)

Solving the differential equation and using the fact that the adoption rate reaches a maximum at time at a point t_0 (Arnold, 2002 and Lund 2006), we get:

$$X(t) = \frac{M}{1 + \exp(-r(t - t_0))} \tag{4.2}$$

where t_0 is the inflection point in the logistic curve or the time at which the adoption rate reaches a maximum. We can observe that this is a special case of the Bass model when we assume $p=0$ and use r in place of q.

To estimate the parameters, M, r and t_0, I used the nonlinear least squares logistic curve fitting technique presented in the tutorial by Arnold (2002). The results are shown in Table 4.1.

Parameters		Estimate
Ceiling of Adoption (kW)	$\boldsymbol{M}$	86107.18
Penetration rate	$\boldsymbol{r}$	0.116898
Time of peak sales (Inflection point)	$\boldsymbol{t_0}$	49.587

Table 4.1 Parameter estimates of the logistic model used to fit the quarterly cumulative installed capacity for residential systems in Austin

As the results indicate, the estimated maximum ceiling of adoption of residential solar PV according to the Logistic fit is 86.107 MW[14]. However, it should be noted that this forecast is based on data from a very early stage in the program as indicated in Figure 4.4. As more data becomes available on the future progress of the program, a better fit might give a higher ceiling of adoption and accurate estimates for r and t_0. The model predicts that the maximum installed capacity in a quarter (rate of adoption) would peak at 2483 kW in the third quarter of 2016. Figure 4.2 shows the actual quarterly installed capacity along with the logistic model fit and Figure 4.3 shows the cumulative installed capacity with the model estimates.

[14] Austin Energy's solar target for 2020 is 200 MW. It is unclear whether this is the target for only distributed solar or if it includes utility scale solar generation.

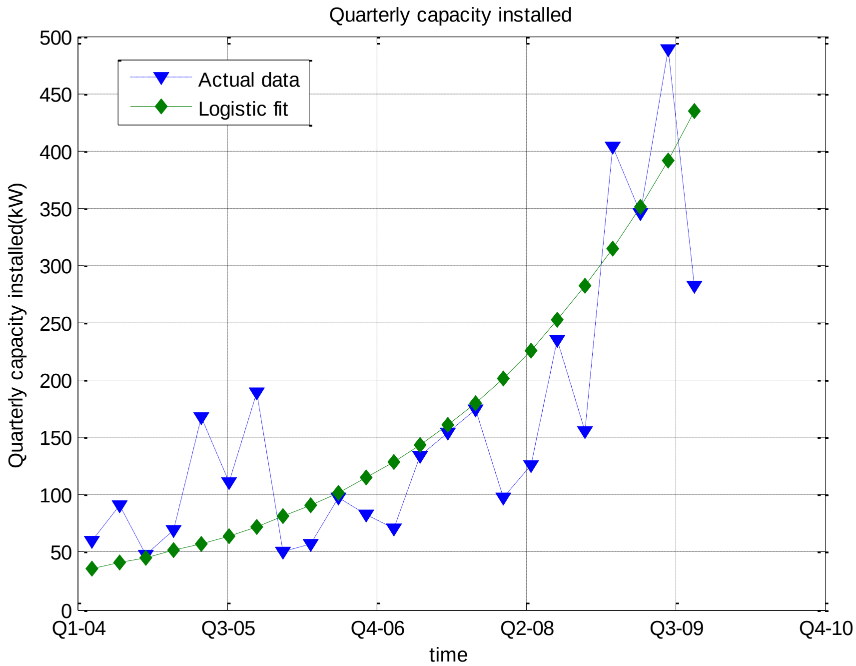

Figure 4.2 Quarterly installed capacity data with the Logistic model fit for residential PV systems in Austin from 2004 to 2009

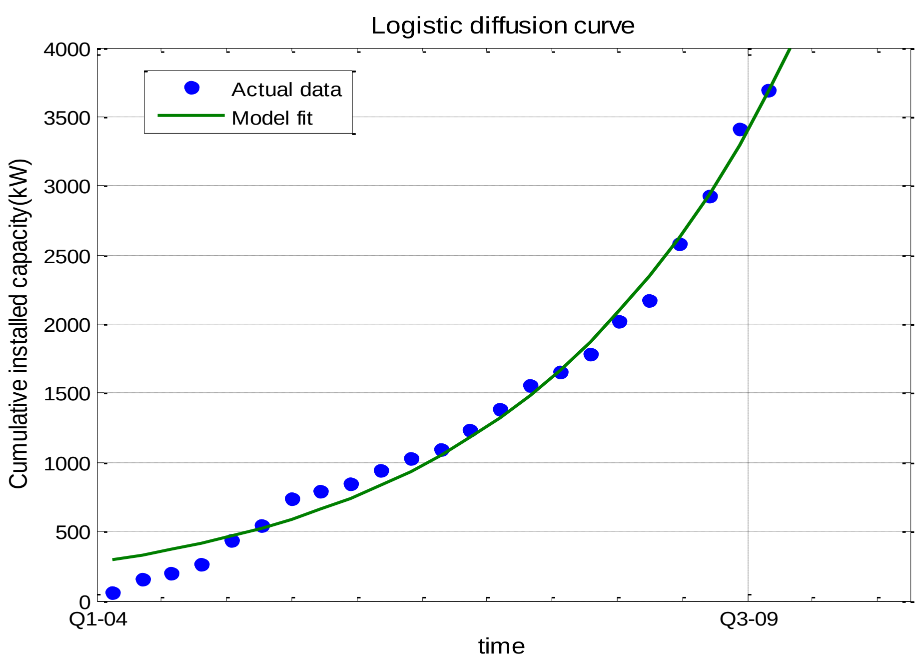

Figure 4.3 Quarterly cumulative installed capacity data and the Logistic model curve for residential PV systems in Austin from 2004 to 2009

Figure 4.4 shows the forecast with the logistic growth equation. As is evident from the plot, the actual data that is used to make the forecast (blue circles) is from a very early stage in the program and therefore the forecast errors could be very large. These estimates could also be the result of misspecification of the model with the logistic equation. In an alternative specification for the logistic model, we can fix the value of M at the maximum potential for residential PV systems as estimated by the Austin Energy study (Wiese, Libby, Long, & Ryan, 2010) at 950,000 kW and estimate the parameters r and t_0.

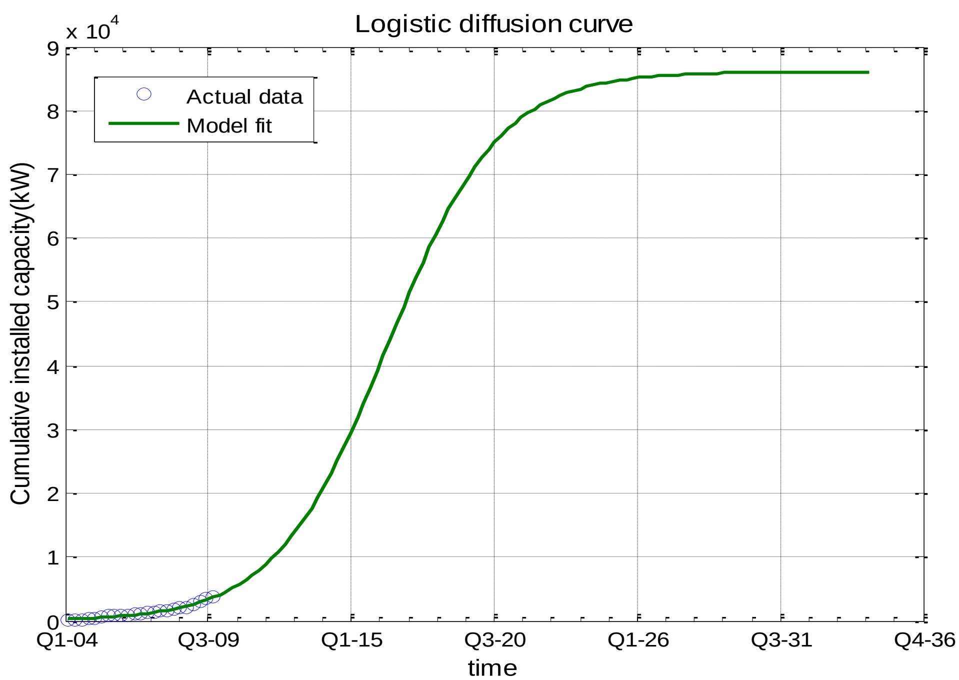

Figure 4.4 Logistic model with forecast for cumulative residential installed capacity and actual data points used for the forecast

4.2 Bass model Without Price Effects

In this section, I used the simple Bass model without any price effects (copied below) to model the quarterly installation data. The value for M=950000 kW is taken from the Austin Energy study that calculated the solar PV for potential for single family residential homes (Wiese, Libby, Long, & Ryan, 2010).

$$S_t = \left(M - X(t-1)\right)\frac{[F(t) - F(t-1)]}{1 - F(t-1)} + \varepsilon_t$$

where

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}$$

S_t – installed capacity in the period from '*t-1*' to '*t*'

X(t-1)-cumulative installed capacity until time '*t-1*'

p and *q* – coefficient of innovation and imitation, respectively

The results using the NLIN procedure in SAS are shown below:

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Approx Pr > F**
Model	2	791897	395948	74.91	<.0001
Error	20	105708	5285.4		
Uncorrected Total	22	897605			

Parameter	**Estimate**	**Approx Std Err**	**Approx 95% Confidence Limits**	
p	**0.000041**	0.000016	7.981E-6	0.000074
q	**0.1018**	0.0206	0.0588	0.1448

The values of *p* (coefficient of innovation) and *q* (coefficient of imitation) are very small indicating the slow rate of growth of PV in Austin. The reason for relatively small values for PV might also be because of the lack of sufficient data to fit the model. The reported standard errors and 95% confidence intervals are asymptotic. These standard errors would be valid only for an infinite sample size and are only approximate for the finite sample used in the model. A goodness of fit statistic for the nonlinear model

(Pseudo-R^2) similar to that of R-squared for a linear model can be calculated using the formula:

$$Pseudo\ R^2 = (1 - \frac{sum\ of\ squares - residual}{sum\ of\ squares - total})$$

$$Pseudo\ R^2 = \left(1 - \frac{105708}{897605}\right) = 0.8822$$

Currently all the data used to fit the model is from the initial section of the S-curve as indicated in Figure 4.7. As more data about the progress of PV installations becomes available, a better estimate for p and q could be calculated. These values are used to forecast the S-curve for adoption and the chart is shown in figure 4.7. The actual cumulative installed capacity and the model prediction taken from the initial section of 4.7 are shown in figure 4.5.

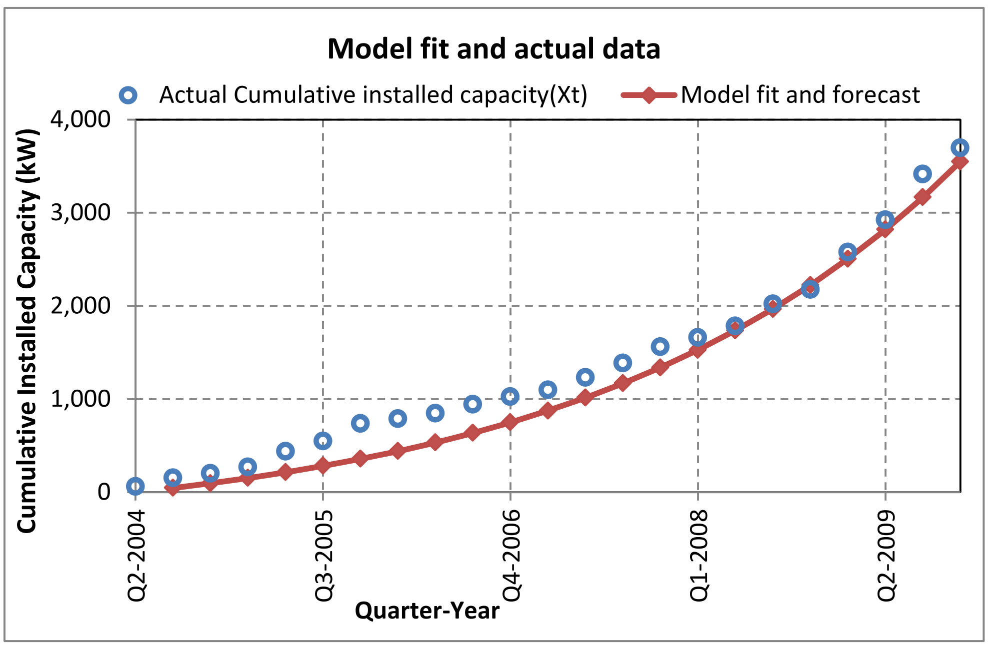

Figure 4.5 Actual and predicted quarterly cumulative installed capacity using Bass model without price effects for residential PV systems in Austin from 2004 to 2009

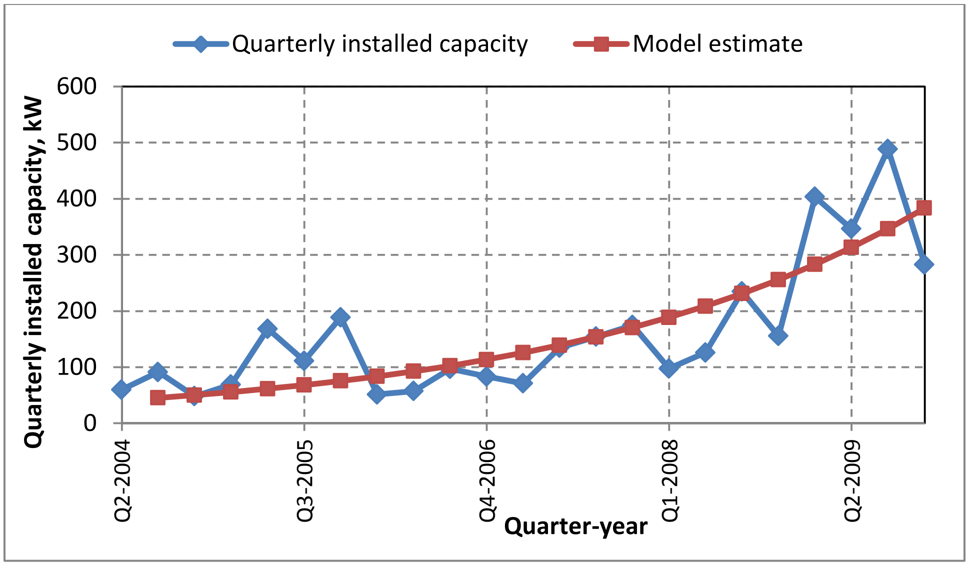

Figure 4.6 Quarterly installed capacity and the Bass model prediction for residential PV systems in Austin from 2004 to 2009

Figure 4.6 shows the installed capacity in each quarter along with the model estimates. The model predicts that the cumulative installed capacity will reach a saturated state around 2036. The time of peak adoption rate, when the adoption rate reaches a maximum can be calculated using equation 3.14:

$$T^* = \frac{1}{(p+q)} \log\left({}^{q}/_{p}\right) = 76.75 \approx 77$$

77 quarters from the starting point of our time series (2004-q2) occurs in 2023 when the installed capacity is predicted to reach the maximum in the second quarter at 24200 kW.

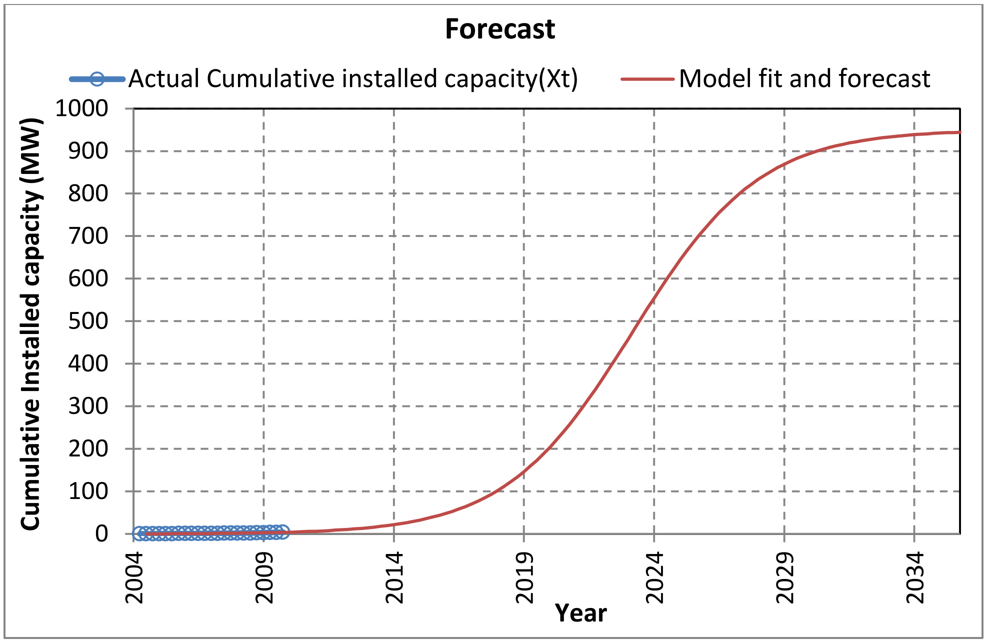

Figure 4.7 Forecast of cumulative installed capacity using Bass model without price effects

As Figure 4.6 indicates, the model fit is still a smoothed curve since it does not include price effects. In the following section, we include the effect of installed cost to estimate the model.

4.3 Model with Price effects

In order to more accurately estimate the quarterly installed capacity and to get a better overall fit, we change the specification of the model to include the installed cost (as the proxy for price) as proposed by Jain & Rao (1990). Going back to equation (3.13) shown below:

$$S_t = \big(M - X(t-1)\big)\frac{c[F(t) - F(t-1)]}{1 - c.F(t-1)} + \varepsilon_t$$

The hypothesis is that an individual's eventual probability of adoption 'c' is now a function of price $c(P_t)$. They proposed the following functional form for $c(P_t)$ (since c is the eventual probability of adoption, its value needs to be between 0 and 1):

$$\log\left[\frac{c(P_t)}{1-c(P_t)}\right]=\alpha+\beta\log P_t \tag{4.3}$$

Equation (4.3) can be rewritten using the definition of a logarithm as:

$$c(P_t)=\frac{1}{[1+e^{-(\alpha+\beta\log P_t)}]} \tag{4.4}$$

Equation (3.13) now becomes:

$$S_t=\left(M-X(t-1)\right)\frac{[F(t)-F(t-1)]}{\frac{1}{c(P_t)}-F(t-1)}+\varepsilon_t$$

$$or\quad S_t=\left(M-X(t-1)\right).\,g(p,q,\alpha,\beta,t)+\varepsilon_t \tag{4.5}$$

$$where\quad g(p,q,\alpha,\beta,t)=\frac{[F(t)-F(t-1)]}{1+\exp(-\alpha-\beta logP_t)-F(t-1)}$$

The results of the estimation are:

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Approx Pr > F**
Model	4	802399	200600	37.93	<.0001
Error	18	95205.8	5289.2		
Uncorrected Total	22	897605			

Parameter	**Estimate**	**Approx Std Error**	**Approximate 95% Confidence Limits**	
p	0.000085	0.000051	-0.00002	0.000192
q	0.0716	0.0255	0.0180	0.1251
alpha	31.2530	30.5596	-32.9504	95.4563
beta	-14.6994	14.5128	-45.1897	15.7910

The goodness of fit statistic (Pseudo-Rsq) similar to the one calculated for the model in section (4.2)

$$Pseudo\ R^2=\left(1-\frac{95205.8}{897605}\right)=0.8939$$

This is a slightly better fit compared to the Bass model without price effects. The estimates for α and β have large standard errors, but the estimate for q is significant at the 95% confidence level and p is significant at the 90% confidence level. Figures 4.8 and 4.9 present the model predictions with the actual installed capacity data. As indicated in Figure 4.9, including the installed cost as an explanatory variable captures some of the quarterly variation in the installed capacity.

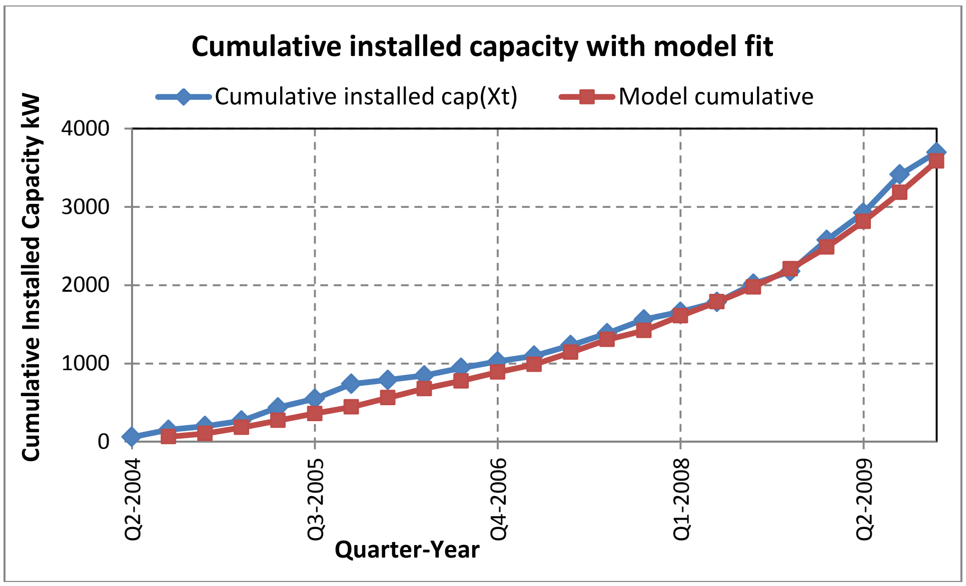

Figure 4.8 Quarterly cumulative installed capacity and predicted values with the Bass model including price effects for residential PV systems in Austin

Although including price as an explanatory variable in the model gives better results, it cannot be used to forecast future adoption without a price forecast. Due to the lack of availability of long term PV price (or installed cost) forecasts, this thesis does not include a forecast for the future path of adoption using this model.

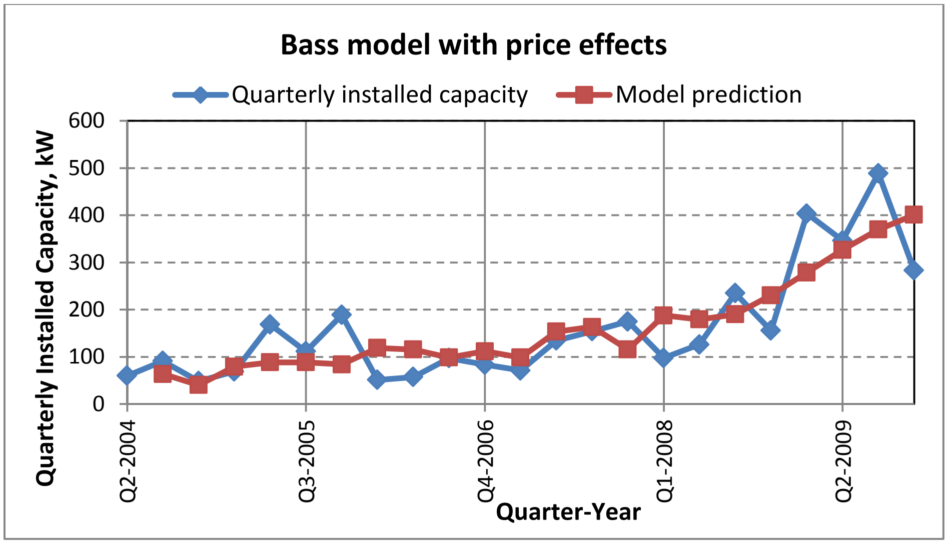

Figure 4.9 Quarterly installed capacity and model prediction with the inclusion of price in the Bass model

The models discussed in this chapter are smoothed curves fit using variations of the logistic growth models. A further improvement on these models would include policy shocks such as changes in rebate levels, changes in federal tax credit rules or net metering rules that might influence a household's decision to install solar PV. It should be noted that to forecast the diffusion, future forecast data on these variables needs to be collected.

Chapter 5: Alternative Tariff

In this chapter, we review the net metering tariff mechanism used by Austin Energy for billing customers with distributed generation and test an alternative tariff mechanism that charges the customer according to the actual grid usage instead of the net energy consumption. We use hourly simulated data for photovoltaic generation profile and load profile data from ERCOT as a proxy for average residential load curve to calculate the difference between the current mechanism and the alternative tariff considered here. Section 5.1 introduces and describes the concept of net metering. Section 5.2 describes the current Austin Energy tariff mechanism and section 5.3 presents the results of a simple calculation to evaluate the difference between the current and alternative tariff.

5.1 Distributed Generation & Net Metering

In the effort to encourage low carbon energy generation, federal, state and local governments have introduced various policies to incentivize the adoption of renewable energy technologies. Some of the technologies like solar photovoltaics and wind turbines have the advantage of being built on a smaller scale compared to conventional power plants, thus enabling consumers to install these systems at the site of consumption. In addition to low carbon emissions, these systems have the advantage of reducing the need for building additional generation and transmission capacity as well as eliminating energy losses in transmission (California Public Utilities Commission, 2010)[15]. These distributed generation (DG) technologies however currently face the problem of high upfront capital costs. To encourage innovation in the manufacturing and installation of these

[15] The report on evaluating the cost effectiveness of net metering in California was prepared by Energy and Environmental Economics, Inc., but the section cited here is the introduction prepared by the CPUC Energy Division.

technologies and lower the costs, governments at federal, state and local level adopted programs to promote these technologies. The key goal of these programs is to promote economies of scale and learning by doing to reduce costs (California Public Utilities Commission).

Solar photovoltaics gained popularity as a customer sited generation technology because of the abundant availability of the solar resource, low environmental impacts, and favorable time pattern of generation because it coincides with the time of the day when electricity is most valuable. Governments have allocated millions of dollars as budget for programs to support incentives for installing solar PV on rooftops in the form of upfront capacity based payments, performance based incentives, solar energy targets and federal and state tax benefits[16]. In addition to these, Net-energy Metering (or more commonly, just net metering), an electricity tariff mechanism designed for the benefit of customers with grid connected distributed generation (DG) technologies has also been instrumental in the growth of PV systems.

Due to the variability of intensity in solar radiation, the power generated by a PV system is not constant throughout the day. At the same time, energy consumption pattern in buildings is also highly variable depending on the usage patterns of various appliances. Due to the variability in both generation and consumption, a customer with grid connected solar PV system may at times draw energy from the utility grid or, export power generated in excess of onsite consumption into the grid. Net metering mechanism allows a customer to sell excess electricity produced by a PV system back to the utility at the retail rate. This is accomplished with meters that run backwards when the PV system generates more electricity than the current consumption level of the customer. The utility

[16] Information on incentives and policies can be found at DSIRE (Database of State Incentives for Renewable Energy) website: http://www.dsireusa.org/

therefore charges the customer for only the net energy drawn from the grid during the billing period. Without on-site energy storage systems, a customer cannot store this energy to use it during those periods when consumption is greater than the PV generation. Without net metering, electricity generated by the PV system in excess of the customer load is of no value to the customer. Therefore, with the intermittency issue and no net metering, customers might be hesitant to install solar PV (or any other DG technology). Having net metering also encourages the customer to select an optimum system size, because without net metering, the customer might be inclined to undersize the system to avoid generating any excess electricity.

5.2 AUSTIN ENERGY'S ELECTRICITY BILL

Currently, Austin Energy's energy bill for residential customers consists of three parts[17]: Customer charge, Energy charge (E01) and Fuel charge. The fuel charge is the cost of generating the electricity supplied by Austin energy. It is directly passed on to the customer, dollar for dollar. Fuel charge includes the fees and charges to be paid to ERCOT, the independent system operator that operates the electric grid, as well as any deficits or excess collections from the previous year. It is estimated based on forecasts of the required power, the plants that would be operated to generate that power and the forecasted sales in kWh. It is calculated as[18]:

$$(Fuel\ Factor)_t = \frac{F_t + I_t}{S_t} + \frac{(F_{t-1} + T_{t-1}) - A_{t-1}}{S_t} \tag{5.1}$$

where: t = the 12 month period for which the fuel rate is being calculated

17 http://www.austinenergy.com/Customer%20Care/Billing/Understanding%20Your%20Residential%20Bill/billCharges.htm

18 Austin Energy's webpage on rates: http://www.austinenergy.com/About%20Us/Rates/fuelAdjustmentClause.htm

F_t = estimated cost of fuels and purchased power (forecast) during time period‘t’

I_t = estimated charges and fees to be paid to ERCOT during time period‘t’

S_t = estimated service area sales of energy in kWh during period ‘t’

F_{t-1}. I_{t-1} = actual cost of fuel and the actual fees and charges paid to ERCOT during the latest 12 month period (t-1)

A_{t-1} = Actual cost recovered by sales for the latest 12 month period

The customer charge is a fixed monthly charge to recover the cost of billing (currently \$6.00 per month). The energy charge recovers the costs of operating and maintaining Austin Energy’s system (distribution), including the debt obligations. Both the fuel charge and the energy charge are calculated based on the kWh consumed in a month, i.e the fuel factor and energy rate are multiplied by the electricity consumed (kWh) in a billing period (a month) and the fixed customer charge is added to this amount to arrive at the monthly electricity bill.

5.3 An Alternative Tariff structure

When there is no distributed generation, *i.e.* no power generated on the customer side of the meter, the current billing structure is accurate, because the fuel charge and the cost of distribution service are directly proportional to the amount of electricity one draws from the grid. The equation for the energy and fuel charge components of the bill (we will ignore the constant customer charge component in the current analysis) can be written as:

$$C = F + D = f.E + d.E = (f + d).E \qquad (5.2)$$

where C = sum of the energy charge and fuel charge in the monthly bill

F = total fuel charge for the billing period (\$)

D = total energy charge for the billing period(distribution service, debt obligations)

f = the per unit fuel factor ($/kWh)

d = the per unit energy rate (E01) ($/kWh)

E = net energy drawn (equal to total energy drawn) from the grid (kWh)

In the above equation, both the cost of the fuel used to generate as well as the distribution charge are directly proportional to the energy drawn from the grid (because total energy consumed = total energy drawn from the utility grid).

For a customer with rooftop solar PV (or any other generation source on the customer side of the meter), there are times of the year when the customer sited PV generates more energy than that is consumed on-site. In this case, net metering allows Austin energy to calculate the net amount of energy that a customer draws from the grid during the billing period. Net energy consumed is the difference of the total energy drawn from the grid (when the load is greater than what the PV system generates) and the total energy exported into the grid (when PV generates more energy than the on-site consumption). Austin Energy currently calculates the fuel and energy charges by multiplying the fuel factor and energy rate with the net energy consumed. The current net metering methodology can be written as the following equation:

$$C = \begin{cases} f.(E_{in} - E_{out}) + d.(E_{in} - E_{out}) = (f + d).(E_{in} - E_{out}) & if\ E_{in} > E_{out} \\ f.(E_{in} - E_{out}) & if\ \ E_{in} < E_{out} \end{cases} \quad (5.3)$$

where: E_{in} = total energy drawn from the grid during the one month period

E_{out} = total energy exported back into the grid during the one month period

Note that in the above formula, the second part, when E_{in} is less than E_{out}, (E_{in}-E_{out}) is negative, which reflects a credit to the customer. When the customer generates more than his consumption in a month, that is the net energy flow is from the customer to the grid, he is paid the fuel charge during the period. This compensation is based on the avoided cost for the utility.

In the above equation, the fuel charge is accurately calculated because the customer is paying for the actual cost of generating the electricity that the household consumed. In the case of the energy rate (which accounts for the cost of providing distribution service) the customer with a solar PV is not charged according to his 'grid usage'. This is because the actual grid usage (that accounts for the distribution charge) is now NOT directly proportional to the net energy drawn from the grid. It is actually a complicated function of how much energy the PV system generates, during what times it is being generated and the load curve of the customer (the energy consumption pattern during different time periods of the day). An alternative tariff mechanism would be to calculate the energy charge according to the actual 'grid usage' instead of the net kWh drawn from the grid. Without distributed generation, the actual grid usage is the same as the kWh drawn from the grid. Although most electricity meters give an accurate account of the net energy drawn from the grid during the billing period, they do not give an accurate estimate of how much electricity is flowing both ways, unless there are two separate meters that record energy drawn from the grid and energy exported to the grid.

For a customer with rooftop PV, we propose a simple method to calculate the actual grid usage, on which to base the energy charge. Although it is complicated to calculate the exact amount of grid usage (unless a smart meter records both the energy consumed as well as PV generation in each time interval), we can approximately estimate the actual grid usage by a customer with a rooftop solar PV system by estimating an hourly PV generation curve as well as an hourly load curve. (There are some monitoring devices available in the market that perform the same function and allow the customer to look at the pattern of generation and consumption on the web[19]). If, during any given hour (or if possible, a finer time interval), the PV system generated more electricity than what was consumed onsite, the excess electricity is transmitted into the grid. If the consumer's load was more than the PV generation, energy is drawn from the grid. During both these time intervals, the customer is using the grid to either draw from or export energy into the distribution grid. Therefore, the alternative tariff structure considered here would charge the customer based on the actual grid usage (which is the sum of the hourly energy drawn and excess energy exported into the grid) instead of the net energy consumed (which subtracts the energy exported into the grid from the energy drawn from the grid).

The alternative energy charge calculation can be written as:

$$C = f.(E_{in} - E_{out}) + d.(E_{in} + E_{out}) \tag{5.4}$$

Unlike Equation 5.3 that shows the current tariff, this single formula accounts for both the cases when E_{in} is greater than or less than E_{out}.

5.4 Data, Methodology and Assumptions

In order to calculate the E_{in} and E_{out} values, we use hourly simulated PV generation curve and hourly load data (energy consumption by the household). This allows us to calculate the net energy drawn (or exported) in each hour of the day. This is still not the most accurate estimate because PV generation is highly sensitive to cloud cover and shading and therefore intra hour variations are not accounted for, but given the constraints in data availability, this gives us a good starting point for the analysis.

[19] For example, eGauge is a very popular monitoring system for solar PV systems: http://www.egauge.net/devices/

The PV generation curves are simulated using the System Advisor Model (SAM) developed at National Renewable Energy Laboratory (NREL)[20]. It uses the TRNSYS[21] Simulation engine to calculate the hourly performance data for a system given the array specifications and weather data. SAM allows us to select the module and inverter models from a database of available models in the market compiled by Sandia National Laboratory and the California Energy Commission. The weather data used is the Typical Meteorological Year 3(TMY3) data compiled by NREL[22]. TMY3 includes the most recent radiance and meteorological data compiled by NREL.

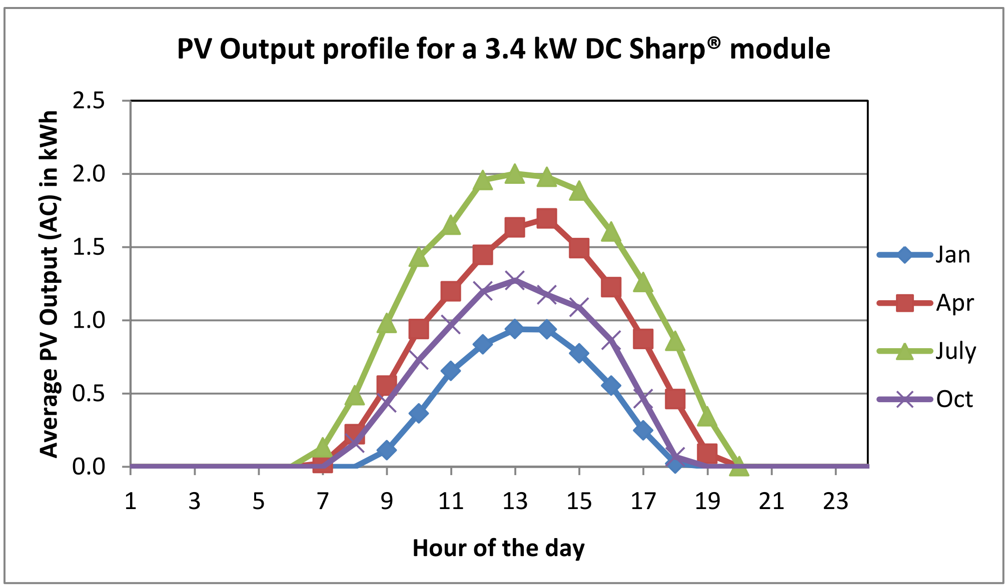

Figure 5.1 Simulated PV generation profile for an example system configuration

Figure 5.1 shows an example simulated PV generation curve for the months of January, April, July and October. It is a plot of the average hourly AC power generated by a PV system of rated capacity 3.4 kW DC STC. The module model is Sharp NE

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[20] Download and documentation for SAM: https://www.nrel.gov/analysis/sam/
[21] TRNSYS was developed at the University of Wisconsin's Solar Energy Laboratory
[22] TMY3 data available at: http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/

170U1® and the inverter model is Fronius IG-3000,(tilt - 10^0 and azimuth – 160^0)[23] a representative system configuration from the available data[24].

The load data comes from ERCOT's 2010 backcasted load profile for south central weather zone and for residential profile type[25]. ERCOT has two categories of load in this profile type: (1) high winter ratio (HIWR) and (2) Low Winter Ratio (LIWR) depending on the ratio of winter to summer load of the consumer[26]. This data is an average hourly consumption profile used by ERCOT for billing and settlement purposes in the electricity market. The ideal dataset that could have been used in this analysis would be the actual residential load data in the city of Austin. Since that data is not available to us, in this study, we proceed with analyzing the alternative tariff with load profile data from ERCOT. The monthly consumption summary for HIWR and LOWR residential loads in 2010 in south central weather zone is shown in Table 5.1.

Using the hourly load data for these two load types (Low winter ratio and high winter ratio), we calculated the net kWh consumed and the actual grid usage as follows:

$$Net\ kWh\ consumed\ in\ a\ month = \sum_{i=1}^{n} E_i \tag{5.5}$$

where E_i is the net kWh drawn from the grid in hour 'i'. E_i is negative if energy is exported to the grid in hour 'i'. n is the number of hours in a billing period (depends on the number of days in a particular month)

$$Actual\ grid\ usage\ in\ a\ month = \sum_{i=1}^{n} |E_i| \tag{5.6}$$

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[23] Ideal orientation for PVs in Austin would be 30 deg tilt and 180 deg azimuth (south facing).
[24] Sharp® modules are used in about 26% of the installed PV systems in Austin (highest share), and about 65% of residential systems overall have rated DC capacity between 3 and 4 kW.
[25] For more information on load profiling, visit: http://www.ercot.com/mktrules/guides/loadprofiling/
[26] Backcast load profile data available at: http://www.ercot.com/mktinfo/loadprofile/alp/

$|E_i|$ is the absolute value of the net energy drawn in hour 'i' and is always positive.

Months	**LOWR net kWh consumption**	**HIWR net kWh consumption**
1	579.05	1555.78
2	457.21	1362.66
3	337.50	694.41
4	402.34	493.51
5	791.89	766.34
6	1121.68	1019.85
7	1143.40	1034.79
8	1418.24	1296.51
9	1018.65	942.50
10	621.99	694.72
11	513.31	814.57
12	549.05	1234.75
YearlyTotal	**8954.32**	**11910.39**

Table 5.1 Monthly kWh consumption by Load profile types

We estimated the energy charge in the monthly bill (fuel charge and customer charge remain the same in both the tariffs) according to the current tariff and the alternative tariff for three cases shown in Table 5.2. The annual energy charge in these three cases was calculated for the two load types considered[27] and the difference between the current and alternative tariffs was estimated for the resulting six scenarios. The results are shown in Table 5.3.

[27] The residential energy rate is $0.0355/kWh for the first 500 kWh and 0.0602 for additional kWH in winter months and $0.0782 for every additional kWH in the summer months.

Case	Module	DC Rating (kW STC)	Inverter	AC STC Rating	Tilt	Azimuth
1	Sharp NE 170U1	3.4	Fronius IG3000	3.196	10	160
2	Kyocera KC167	3.34	PVP 2800	3.24	25	225
3	SolarWorld SW175	3.15	SMA SB3000	3.008	27	180

Table 5.2 Case scenarios considered for energy charge calculations[28,29]

	Case1		**Case2**		**Case3**	
Load profile type	**LoWR**	**HiWR**	**LoWR**	**HiWR**	**LoWR**	**HiWR**
Net kWh consumed	8954.32	11910.39	9590.96	12547.02	9978.49	12934.56
Actual Grid Usage	9768.8	12483.23	10205.74	12998.17	10196.53	13093.71
Current Energy charge	454.42	618.55	494.12	662.31	519.59	689.11
Alternative energy charge	500.12	657.08	532.55	693.79	531.73	699.56
Annual Difference ($)	$ 45.70	$ 38.53	$ 38.43	$ 31.48	$ 12.14	$ 10.45

Table 5.3 Energy charge under current and alternative tariffs, for a one year period for the 3 cases shown in Table 5.2 and the two load types in Table 5.1

As is evident from the results in Table 5.3, the difference in the energy charges depends on the sizing of the PV system, the load pattern of the household considered and the weather conditions. The difference between current and alternative tariff for our sample scenarios considered vary from $45.7 to $10.45 per household per year. With the smaller system size and orientation of the system considered in Case 3, the PV generation

[28] For a discussion on effect of orientation on PV power generation in Austin, refer to Hoff *et. al.*(2006)

[29] Sharp, Kyocera and SolarWorld are the module manufacturers with the greatest market share in residential solar PV systems in Austin with approximately 26%, 21% and 12% respectively.

rarely exceeds the onsite consumption, which is reflected in the higher 'Net kWh consumed' and 'Current Energy charge'. Therefore, even with higher grid usage, the difference between the current and alternative energy charge is much lower compared to the other two cases considered. A simple back of the envelope calculation extrapolating for all residential PV systems in Austin, to calculate the revenue difference for the utility is shown below:

$$\Delta\, Revenue = \frac{\$\, diff.per\ household}{Capacity\ of\ system} \times Total\ installed\ capacity \tag{5.7}$$

Using equation (5.7), the estimated revenue difference for the utility for one year is calculated for the six scenarios considered under the current status of adoption (total residential installed capacity ≈3800kW)

	Case1		**Case2**		**Case3**	
Load profile type	**LoWR**	**HiWR**	**LoWR**	**HiWR**	**LoWR**	**HiWR**
Revenue difference for the utility ($)	$54,336.7	$45,811.6	$45,072.2	$36,921.0	$15,336.4	$13,201.5

Table 5.4 Revenue difference calculated for the sum of all residential systems at current adoption level

As the dollar figures indicate, the revenue difference is very little compared to the total energy charge revenue from customers for Austin Energy[30]. However, these figures hold for the current status of adoption of solar PV which stands at 3.8 MW for residential customers. This also does not include revenue from commercial customers. Under

[30] According to a financial forecast for Austin Energy, total revenue from energy charges is about $600 million
http://www.austinenergy.com/About%20Us/Newsroom/Reports/COAfinancialForecastApril2011.pdf

increased adoption of PV, a quick calculation gives a very rough estimate for the difference in revenues as shown table 5.5 (dollar amounts in thousands). The total difference in revenue at 200 MW of adoption can vary from $694,800 to $2.86 million per year, which might not be such a small amount to ignore. It should be noted once again that these figures are estimated with approximate data to get an idea about the order of magnitude of the additional revenue potentially generated with the alternative tariff.

	Case1		**Case2**		**Case3**	
Level of adoption	**LoWR**	**HiWR**	**LoWR**	**HiWR**	**LoWR**	**HiWR**
200 MW	2,859.82	2,411.14	2,372.22	1,943.21	807.18	694.81
300 MW	4,289.74	3,616.71	3,558.33	2,914.81	1,210.77	1,042.22

Table 5.5 Revenue difference (in thousands of dollars) under higher level of adoption of solar PV

5.5 DISCUSSION ABOUT THE ALTERNATIVE TARIFF

If the energy charge rates are set using a cost of service type mechanism, the per kWh rate level depends on the cost of maintaining and operating the utility and the revenues collected from customers. This is because the net revenue requirement is distributed among the total kWh sales for a customer class (e.g. residential or commercial). We have seen that using the alternative tariff would bring in additional revenues compared to the current tariff; and keeping all other conditions constant, the rate level ($/kWh) for a customer class would decrease, depending on the actual dollar amounts collected. If the current tariff were to continue, then all the customers would be paying a higher rate (albeit, only a small amount greater than the current rate). Effectively, this amounts to an additional subsidy to customers with distributed generation. Compared to the current level of subsidies provided to distributed generation in the form of direct rebates and tax credits, this additional subsidy would add a very small amount. In a future scenario when the direct incentives might end, the additional subsidy because of the current rate structure might be significant.

If the distribution grid is being utilized by a customer with DG for both importing as well as exporting electricity, it makes sense to levy a usage based rate for the distribution charge. However, this argument depends on how the customer with DG is classified. For a utility scale generator, the cost of transmission for getting the electricity to the load territory is paid by the load, not by the generator. If a customer with DG is classified as a generator, then the cost of distribution for the excess energy exported is analogous to the cost of transmission for electricity transported from utility scale generators. Under such classification, it might be justified to charge the rest of the ratepayers (who do not have DG, but are consuming the energy exported by DG owners) the distribution charge for the exported energy.

As increased DG capacity on the customer side of the meter brings about changes to the traditional utility business model, this is one of the questions that need to be further explored.

Chapter 6: Conclusions

Solar photovoltaics have received government support at the local, state and federal level in the form of tax credits, capacity and performance based rebates and net metering agreements. These incentives were introduced to increase the initial market demand for solar PVs that would help the PV industry realize economies of scale in production. The city of Austin started a rebate program for solar photovoltaics in 2004 with one of the highest rebate levels per kW in the country. The program has funded more than 1000 residential PV systems and more than 100 commercial systems. This thesis attempted to track the progress in solar PV installations in the city of Austin by presenting the trends and distributions in capacity, costs and incentives. The average cost as well as the distribution of installed costs points to the realized reduction in cost for the technology.

To design incentive programs more effectively, it is also necessary to use the data on the progress of these programs to estimate possible future paths of adoption. The technology diffusion models used with the residential PV installations in Austin indicate that more data might be necessary to make any reasonable inferences. With the preliminary estimates, the Bass model indicates that the cumulative installed capacity for residential systems could reach a saturation level by approximately 2038-2040. The peak in quarterly installations is expected to occur in 2023. To more accurately fit a model to the data, it is necessary to incorporate the effect of price, incentives and other policy impacts as these variables influence, at an individual level, the decision to adopt an innovation.

In the final part of the thesis, I analyzed an alternative tariff mechanism for the energy charge in the bill to be based on the actual grid usage. The calculations with simulated PV profiles and average load profiles (from ERCOT) indicate that currently there is very little difference in terms of the total revenue for the utility. However, under a future scenario with greater diffusion of photovoltaics, the dollar amount in revenue difference can sum up to the order of magnitude of a few millions. With increased penetration of distributed generation, there is going to be a change in the traditional electric utility model; and tariff mechanisms that charge for the distribution service based on the net energy consumed need to be looked at more closely.

Directions for future research

The calculations for the alternative tariff study can be made more accurate at a number of levels:

- Actual PV generation is highly sensitive to cloud cover and weather patterns and the simulated hourly data does not include these intra hour variations. PV generation data at a finer time interval would more accurately estimate the actual grid usage.
- The load data can also be improved by using actual metered load for customers.
- The extrapolation of sample values to the entire population can be refined by using better sampling and distributions for the type and orientation of the systems installed.
- Finally, the study can be extended to service areas with time of use or other tiered rate structures.

Appendix A

This appendix contains data referenced in the text as well as the data tables used to plot the figures presented in the thesis.

Type of systems	Number of data entries		
	Raw dataset	Removed	Cleaned dataset
Residential	1109	19	1090
Commercial	108	13	95

Table A.1 Raw and cleaned data numbers

Year	Residential		Commercial		Total	
	Number of systems	Installed capacity (kW AC STC)	Number of systems	Installed capacity (kW AC STC)	Number of systems	Installed capacity (kW AC STC)
2004	72	199.36	6	77.41	78	276.77
2005	186	537.52	12	199.47	198	736.99
2006	97	288.76	8	95.93	105	384.69
2007	177	534.53	17	173.36	194	707.89
2008	208	613.76	36	404.20	244	1,017.96
2009	332	1,521.20	28	360.54	360	1,881.74
2010	18	75.26	--	**--**	18	75.26
Total	**1090**	**3,770.38**	**107**	**1310.91**	**1197**	**5,081.29**

Table A.2 Data used for figures 2.1 and 2.2

Year	Average Cost 2010 $/W AC STC	StdDev of Cost	Average system size(kW AC STC)	Number of observations
2004	8.11	1.30	2.77	72
2005	7.82	0.73	2.89	186
2006	7.88	1.10	2.98	97
2007	7.99	1.30	3.02	177
2008	7.87	1.12	2.95	208
2009	6.62	1.39	4.58	332
2010	6.51	1.68	4.18	18

Table A.3 Data used in figures 2.3 and 2.4 for residential systems

Year	Average Cost 2010 $/W AC STC	StdDev of Cost	Average system size(kW AC STC)	Number of observations
2004	7.43	0.85	12.90	6
2005	8.10	2.54	17.91	11
2006	8.52	1.16	13.65	7
2007	8.13	0.97	12.90	10
2008	8.02	1.38	12.25	33
2009	7.81	1.54	12.88	28

Table A.4 Data used in figure 2.5 for commercial systems

System Size(kW)	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	>16
2004	9.90	7.91	7.17	--	--	7.43	--	--	7.72
2005	9.00	7.71	10.49	--	--	10.30	--	6.61	7.40
2006	10.67	7.73	9.37	8.10	8.20	7.44	8.60	10.84	7.63
2007	8.59	8.00	6.94	--	--	7.49	7.40	7.38	7.85
2008	8.91	7.83	7.85	7.43	8.36	8.19	8.06	6.27	7.35
2009	8.26	6.95	6.53	6.18	6.14	6.12	6.71	5.78	7.22

Table A.5 Data used in figure 2.6 - cost trends for different system sizes

System Size	Average cost ($/W AC STC) in 2009
0-2	8.26
2-4	6.95
4-6	6.53
6-8	6.18
8-10	6.14
10-12	6.12
12-14	6.71
14-16	5.78
>16	7.22

Table A.6 Average cost data in 2009 used in Figure 2.7

Installed Capacity bins (kW)	2004	2005	2006	2007	2008	2009	2010
0-2	9.7%	7.5%	4.1%	4.5%	5.8%	2.1%	11.1%
2-4	88.9%	90.9%	92.8%	93.2%	91.8%	52.1%	33.3%
4-6	1.4%	1.1%	2.1%	1.1%	1.4%	21.1%	38.9%
6-8	0.0%	0.0%	1.0%	0.0%	1.0%	14.8%	16.7%
8-10	0.0%	0.0%	0.0%	0.0%	0.0%	5.7%	0.0%
10-12	0.0%	0.5%	0.0%	0.6%	0.0%	2.1%	0.0%
12-14	0.0%	0.0%	0.0%	0.0%	0.0%	2.1%	0.0%
14-16	0.0%	0.0%	0.0%	0.6%	0.0%	0.0%	0.0%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Table A.7 Frequency distribution of residential systems in capacity bins (Figure 2.8)

Installed cost bins $2010/W AC STC	2004	2005	2006	2007	2008	2009	2010
3-4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.6%
4-5	0.0%	0.0%	0.0%	0.0%	0.0%	9.0%	16.7%
5-6	0.0%	0.0%	1.0%	0.6%	0.0%	21.7%	22.2%
6-7	2.8%	5.9%	8.2%	8.5%	12.0%	36.4%	11.1%
7-8	58.3%	65.6%	63.9%	59.3%	52.9%	21.1%	22.2%
8-9	31.9%	21.0%	18.6%	16.4%	25.0%	8.7%	11.1%
9-10	4.2%	5.9%	5.2%	9.6%	6.7%	1.2%	11.1%
10-11	0.0%	1.6%	0.0%	2.8%	1.4%	0.6%	0.0%
11-12	1.4%	0.0%	0.0%	0.6%	0.0%	0.3%	0.0%
12-13	0.0%	0.0%	2.1%	0.6%	1.0%	0.0%	0.0%
13-14	0.0%	0.0%	1.0%	1.1%	0.5%	0.0%	0.0%
14-15	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%
15-16	0.0%	0.0%	0.0%	0.0%	0.5%	0.6%	0.0%
16-17	0.0%	0.0%	0.0%	0.6%	0.0%	0.0%	0.0%
17-18	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Table A.8 Distribution of installed costs for residential systems (Figure 2.9)

Appendix B

Federal tax credit calculation

This appendix contains the assumptions and methodology for calculating the federal tax credit for the systems analyzed in the thesis. It is based on the 'Frequently Asked Questions on Federal Solar Energy Incentives' document published by the Solar Energy Industries Association[31,32].

- **Residential customers**

The federal personal tax credit for residential customers began in 2006 at 30 % of the installed cost after netting any utility rebates with a cap of $2000. The cap was removed starting in 2009. For individuals, the utility rebate is not considered taxable income and so the tax credit applies to only the expense for the PV system that is taxable.

- **Commercial customers**

For commercial customers, the utility rebate is considered taxable and so the basis for calculating the investment tax credit is the gross installed cost of the system. Prior to 2006, there was a 10% tax credit and it was raised to 30% starting in 2006. There was never a cap on the tax credit amount.

The eligibility for the tax credits is based on 'the date placed in service'. Based on the dataset we have we assumed that the date of final inspection by the utility is the date that it is placed in service.

Conversion to standard 2010 dollars

The costs and rebate amounts are converted to 2010 dollars be dividing the costin a particular year by the CPI for that year normalized to 2010 (these values are given in Table B.1)

[31] Refer: http://www.sunwize.com/buy/pdf/federalfaq.pdf
[32] http://www.sunnovations.com/sites/default/files/SEIATaxManual_v3-0_FAQ.pdf

For example, the formula to convert 2004 dollars amount into 2010 dollars is:

$$Cost\ in\ 2010\ \$ = \text{Cost in 2004 \$}/0.866$$

Year	Annual Avg.	CPI Normalized to 2010
2004	188.9	0.866
2005	195.3	0.896
2006	201.6	0.925
2007	207.342	0.951
2008	215.303	0.987
2009	214.537	0.984
2010	218.056	1.000

Table B.1 The annual average CPI data and CPI normalized to 2010

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Vita

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